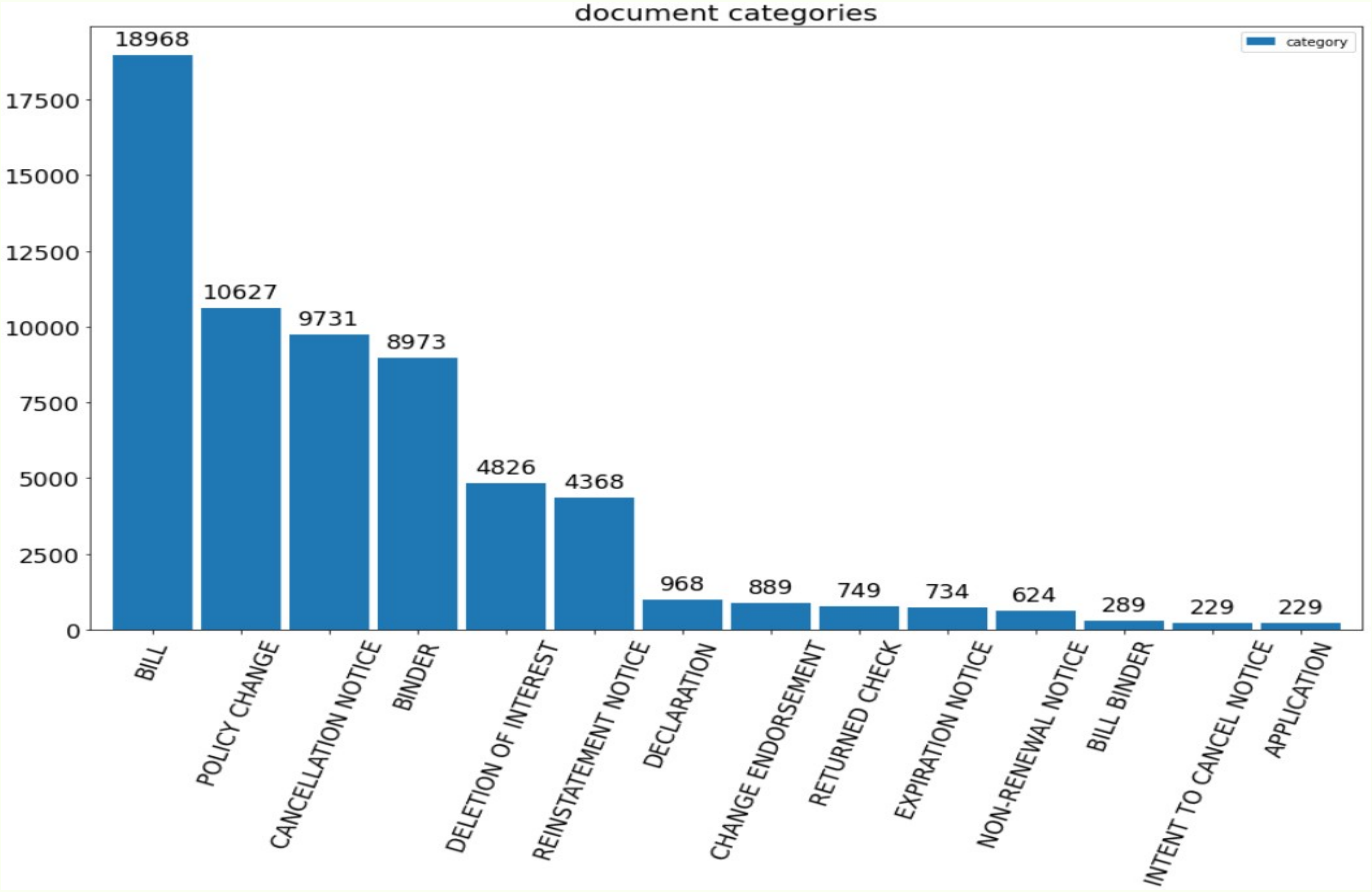
HeavyWater Machine Learning Problem

Solution by Mark Wilber

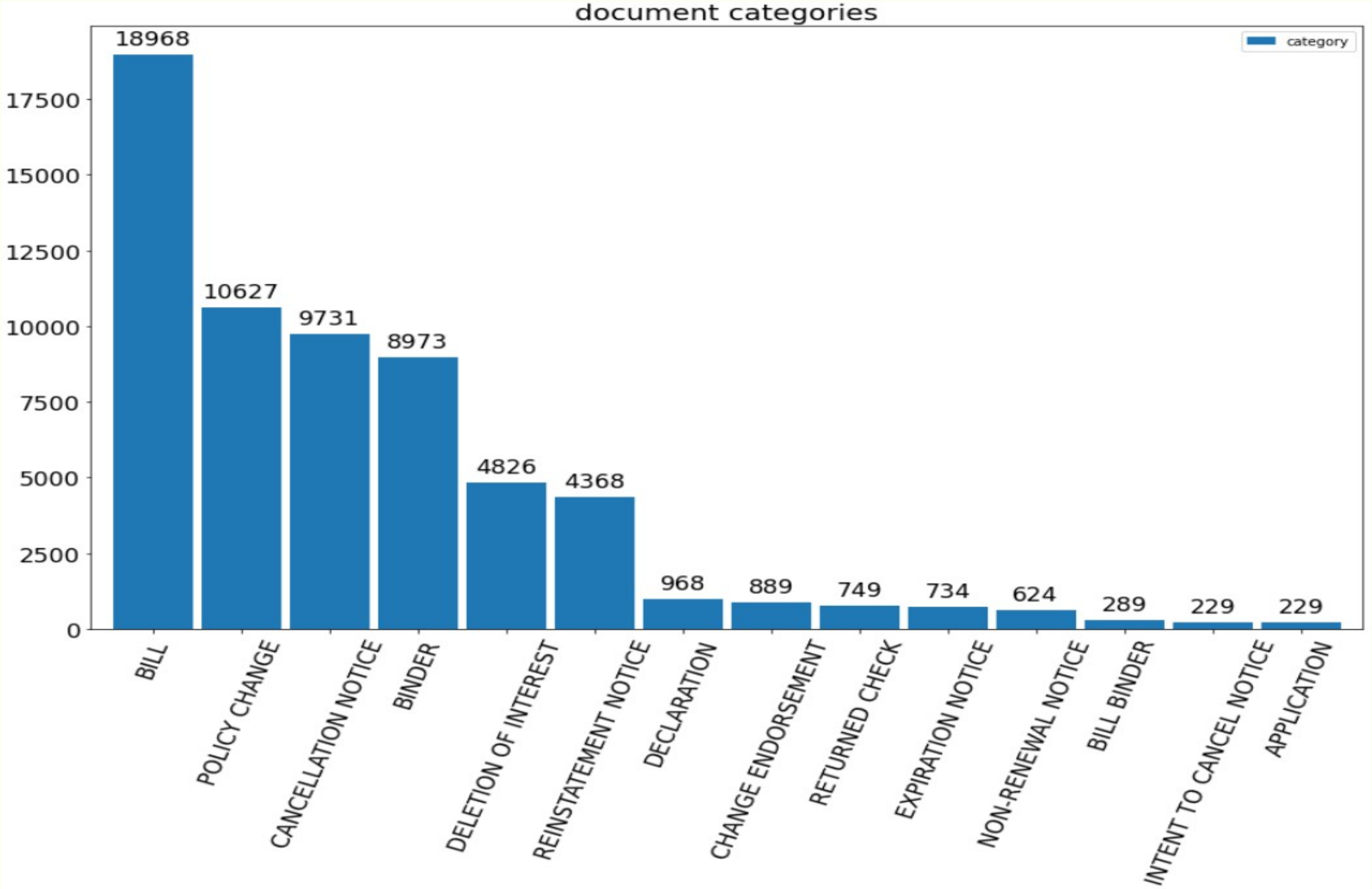
What we are dealing with

- 62,204 documents, 14 categories



What we are dealing with

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



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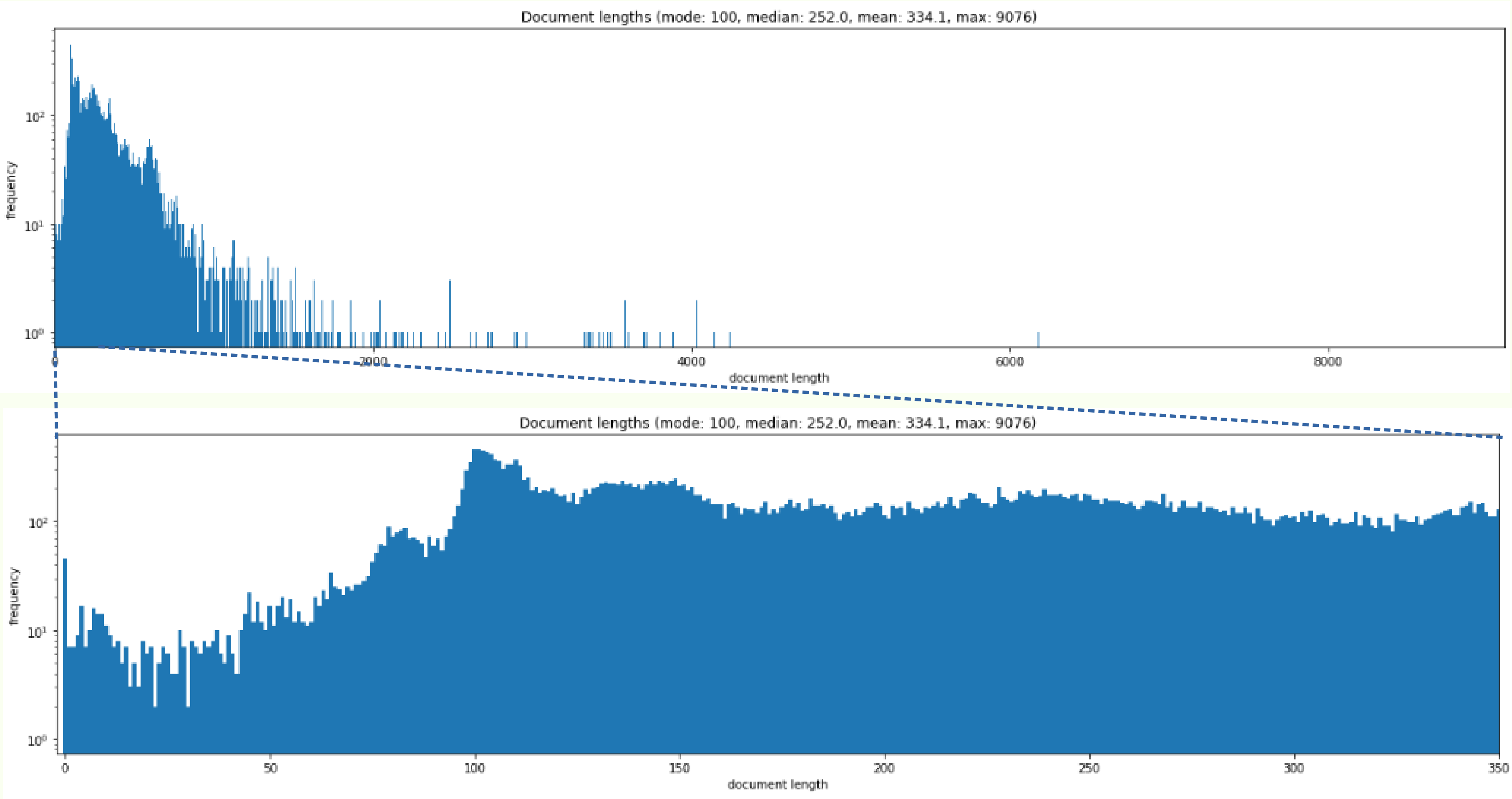
- document lengths spanning 0–9076 tokens (mode: 100, median: 252, mean: 334.1)



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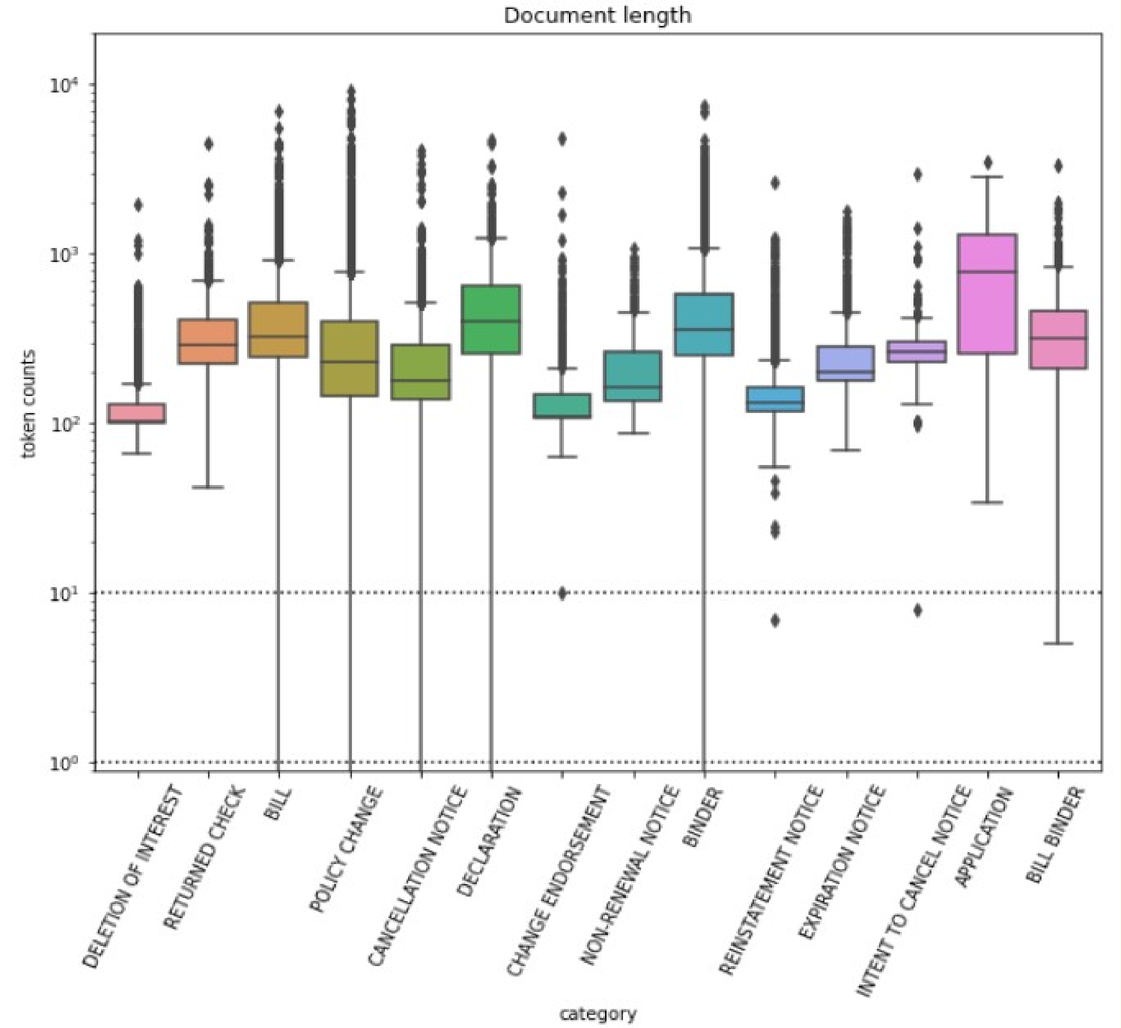
- document lengths vary widely by category, but few are shorter than 10 tokens



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

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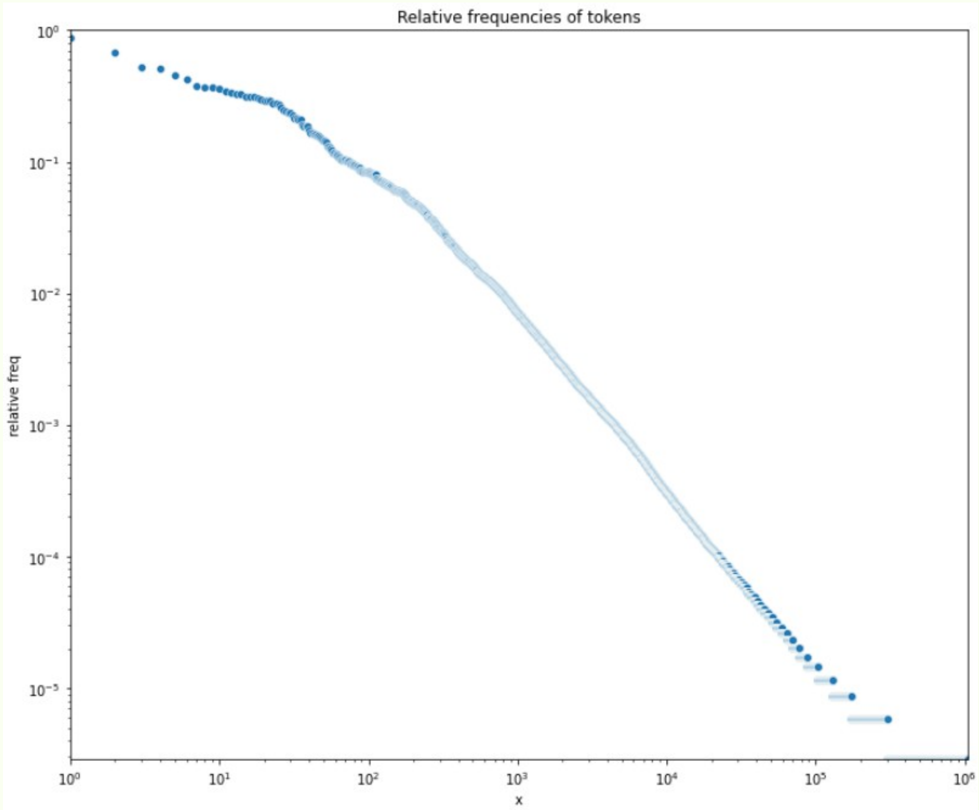
- Most frequent terms don't follow Zipf's relation



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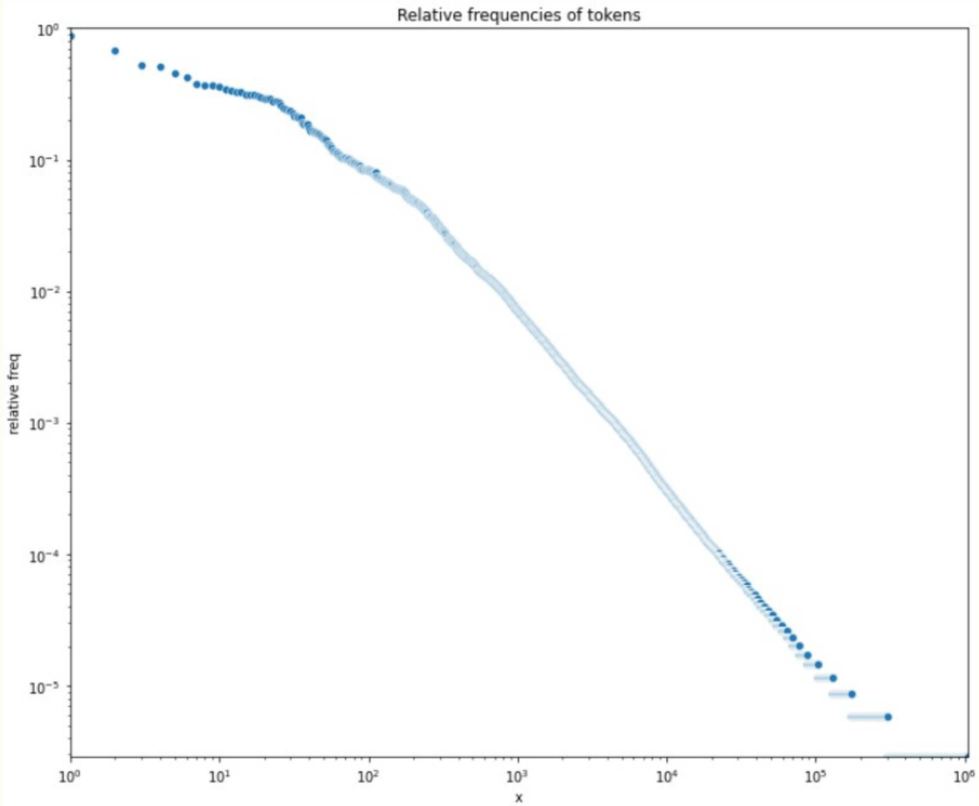

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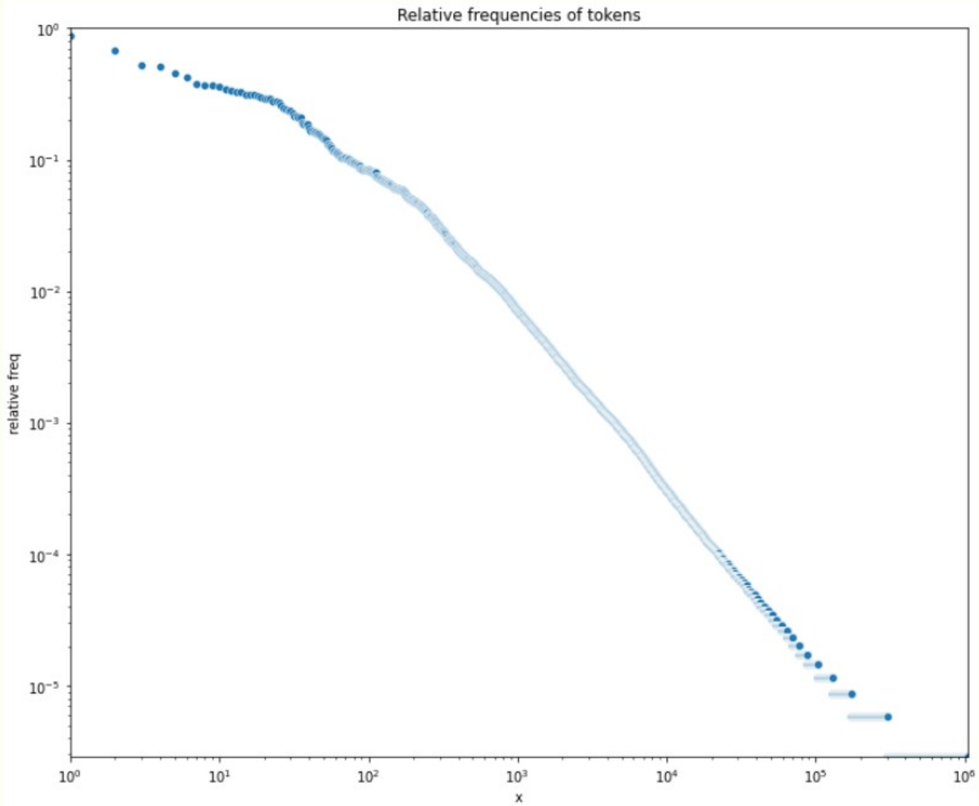

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⇨ *this corpus seems to be unusual ...*

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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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	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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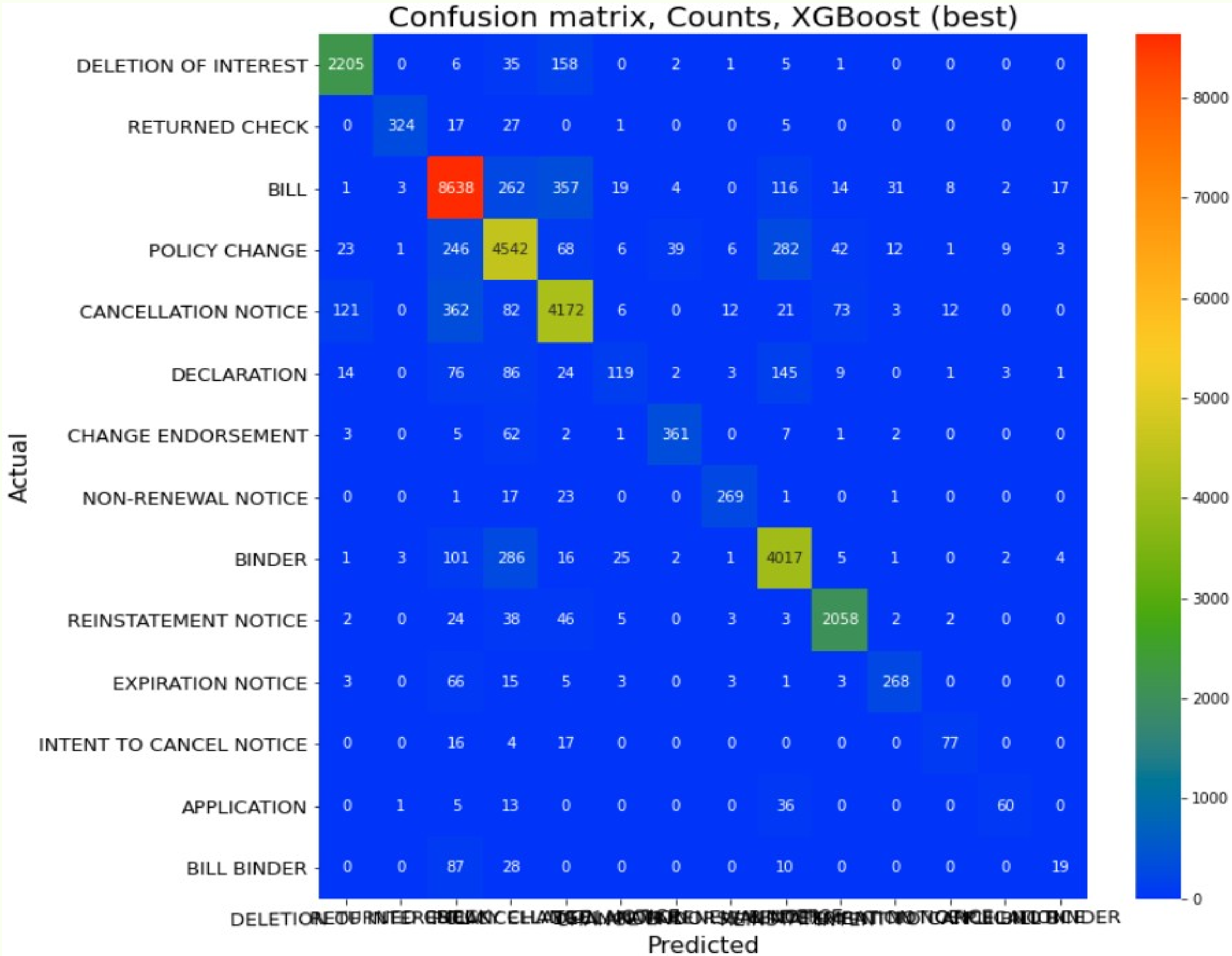

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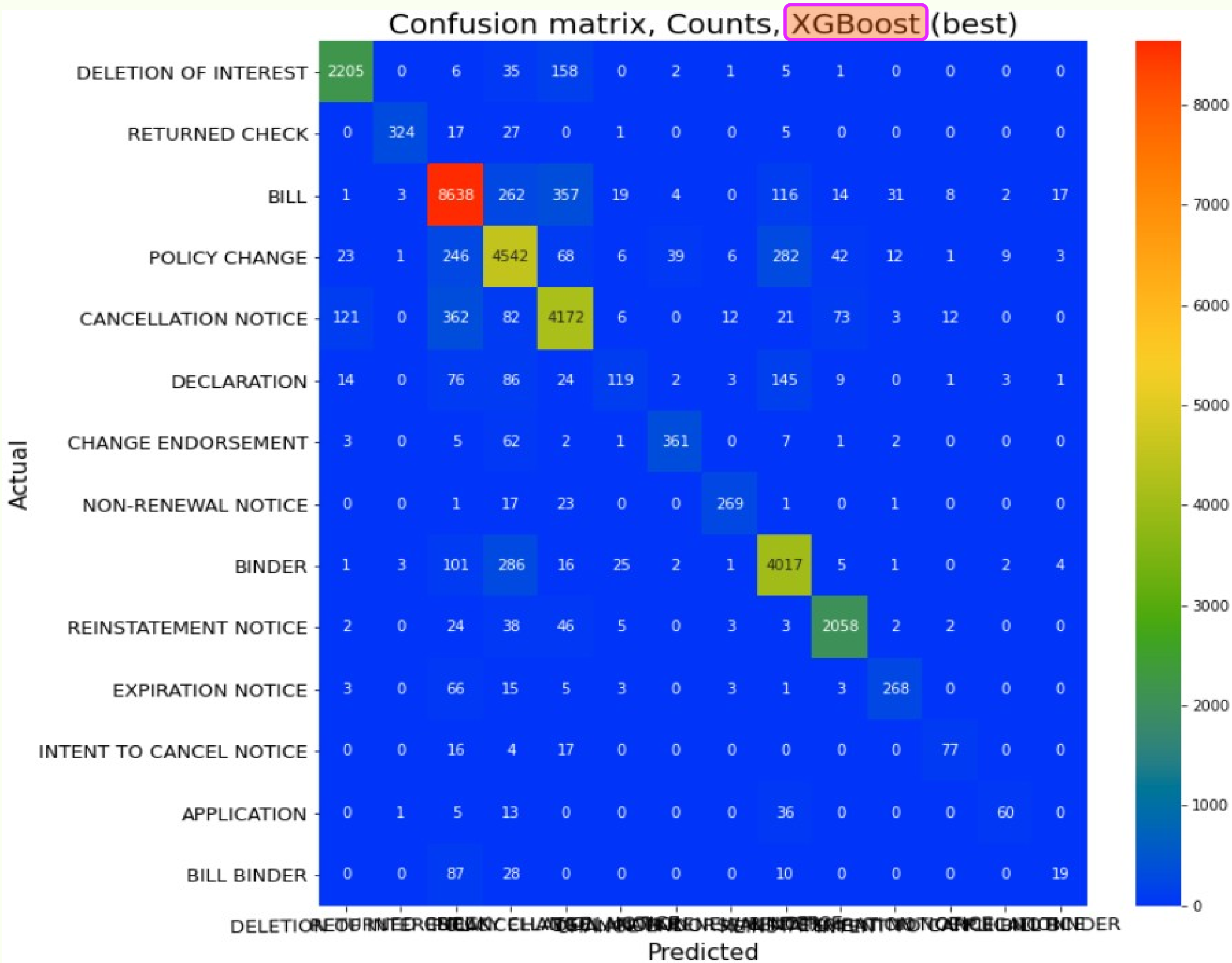

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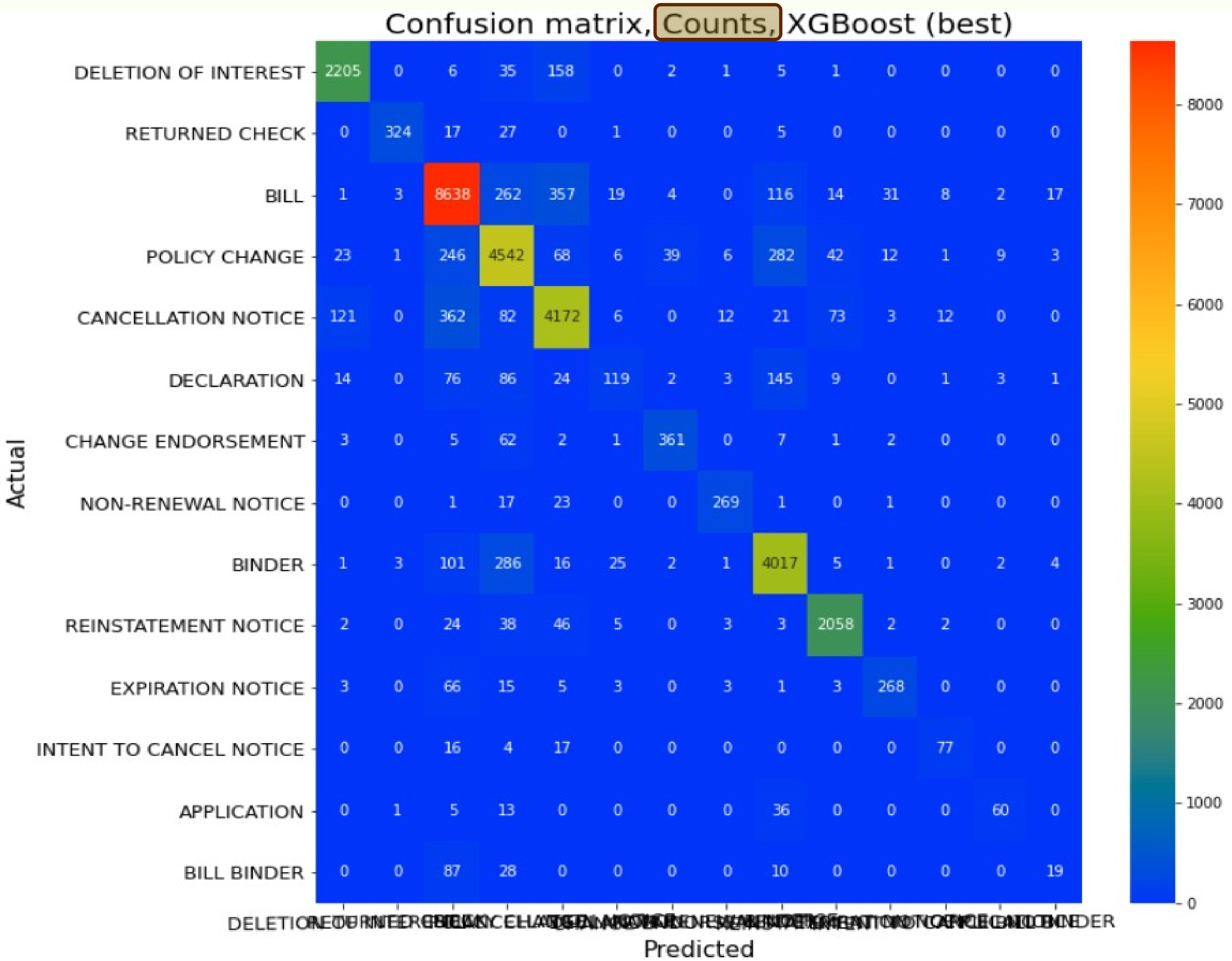

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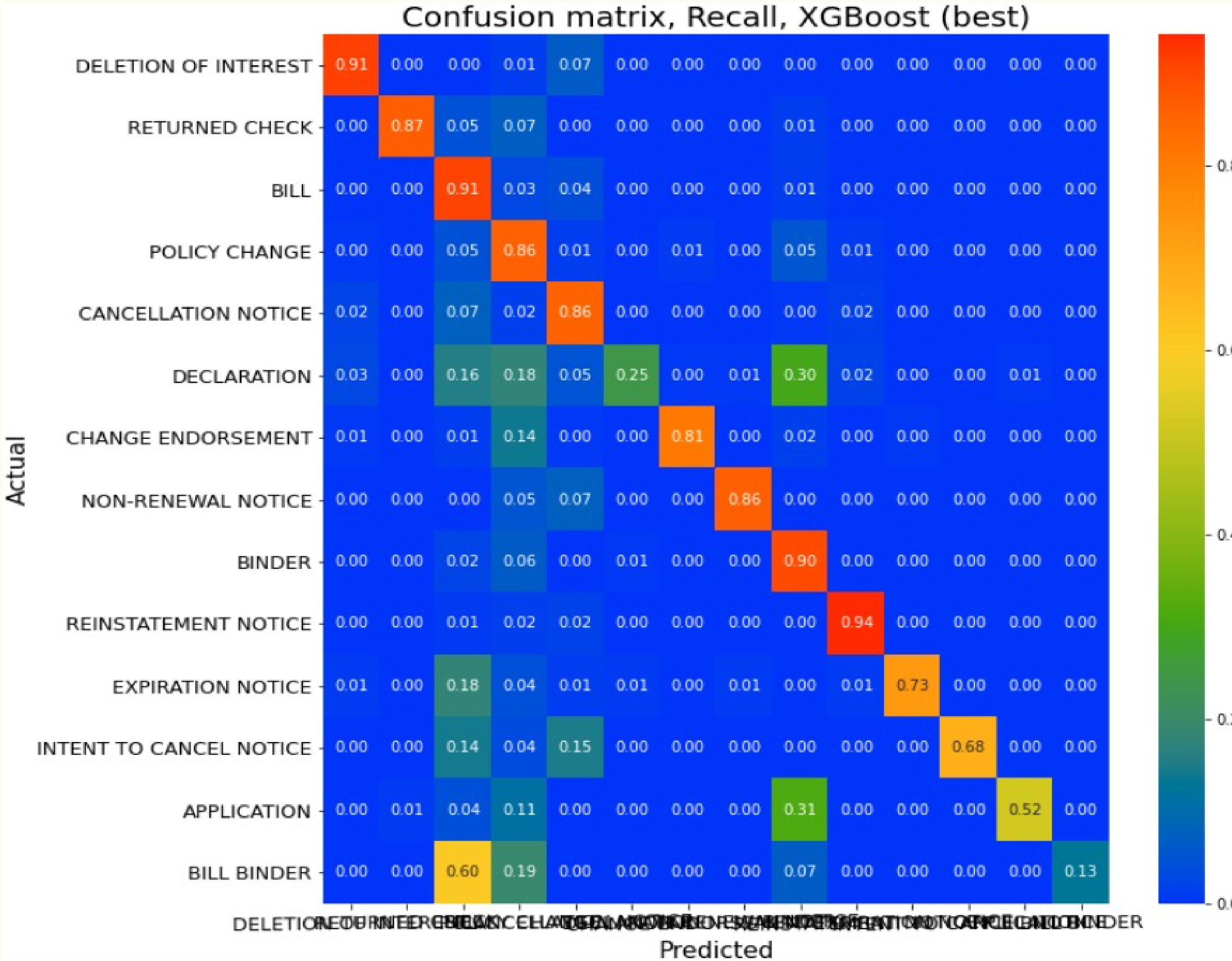

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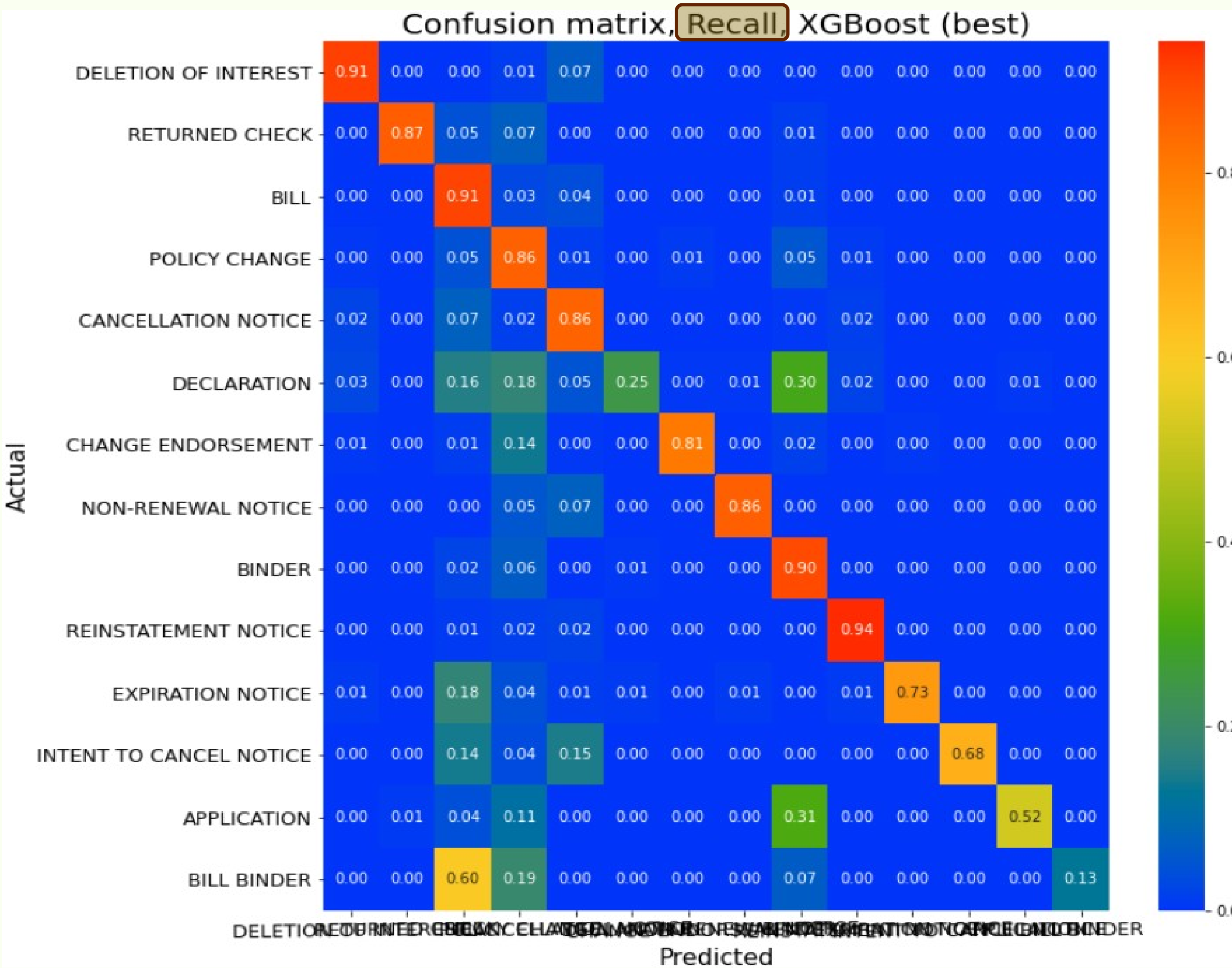

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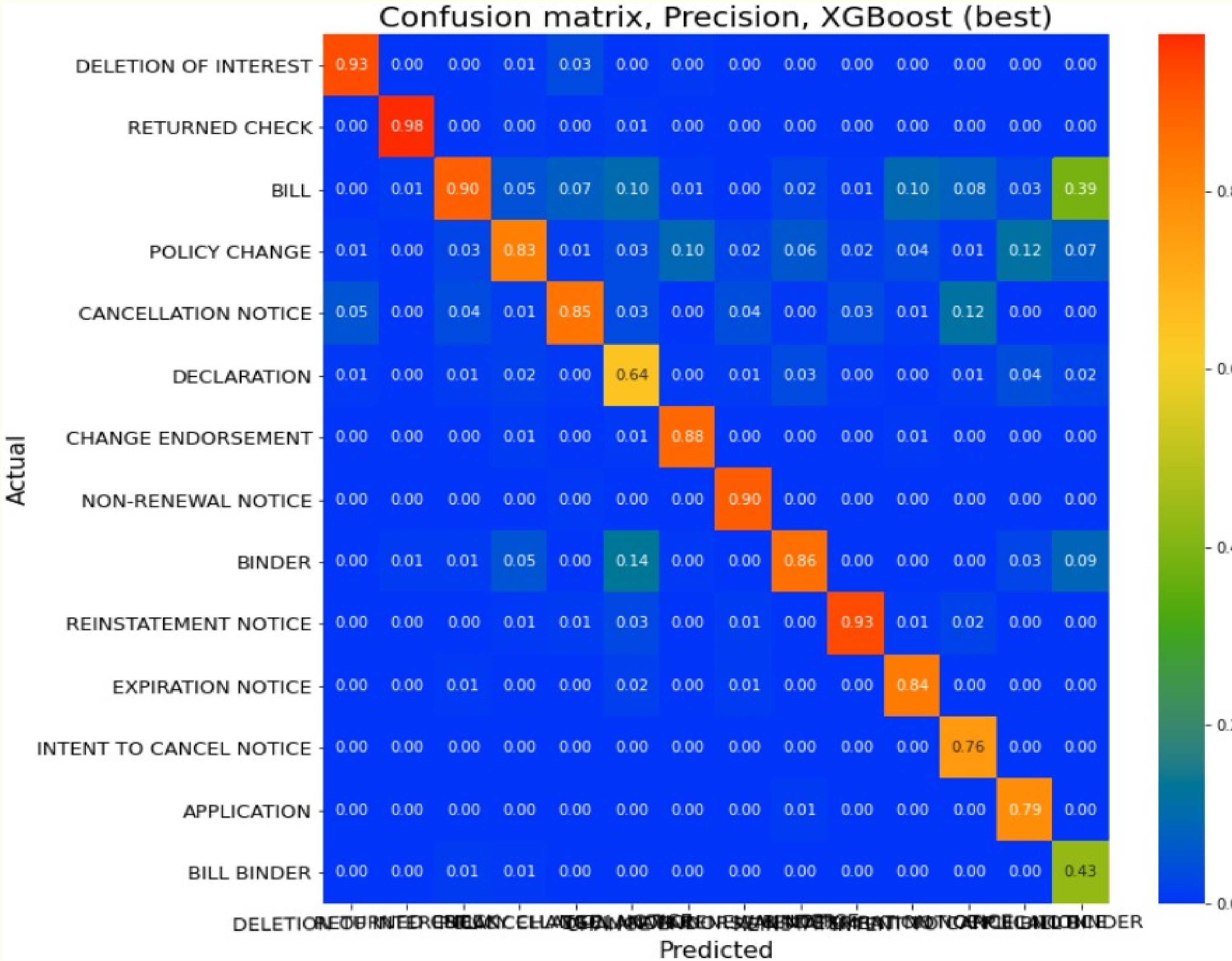

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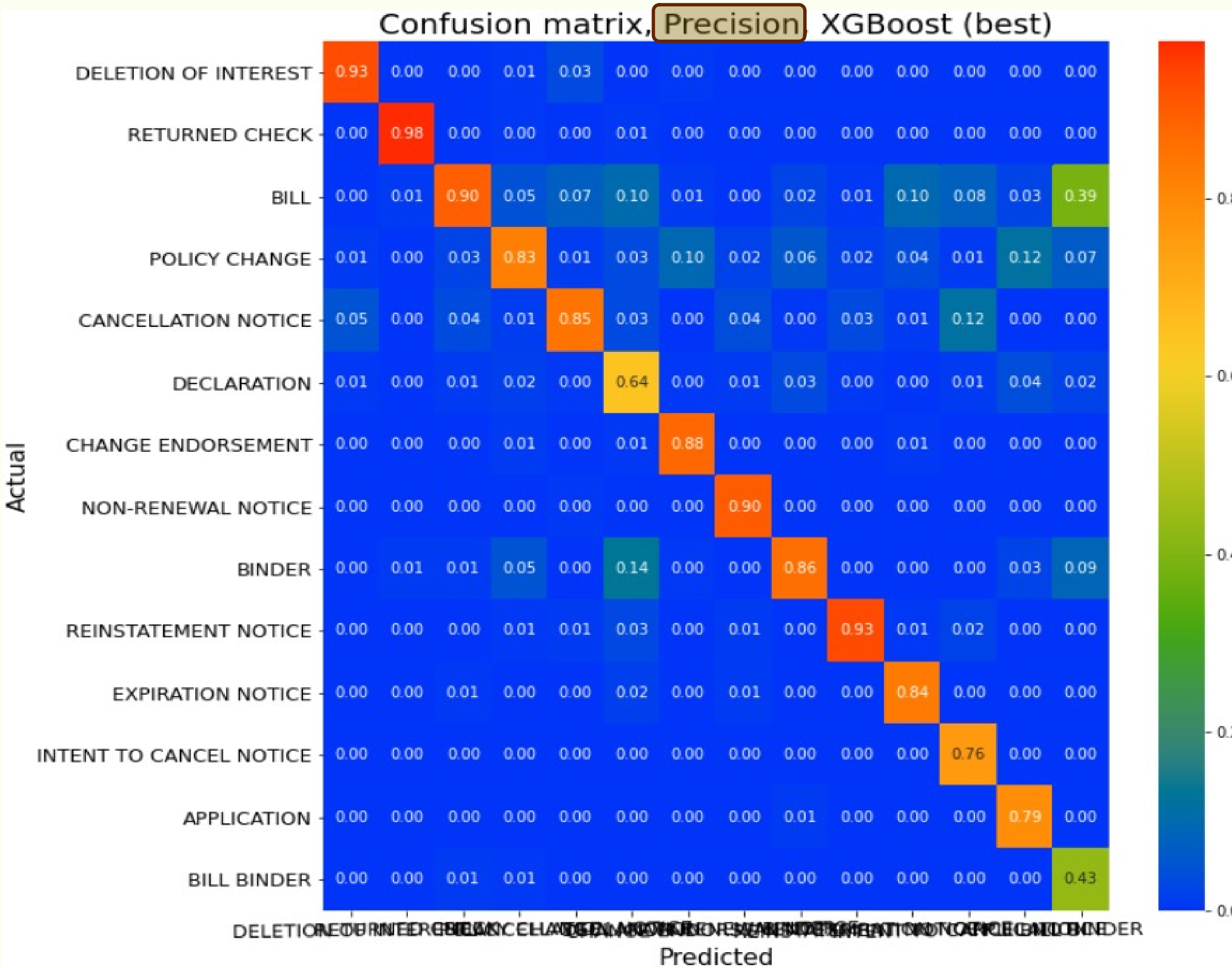

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Deployed Solution

General notes

- Find code in [github repo]
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  - ⇨ trained model insisted on GPUS for inference
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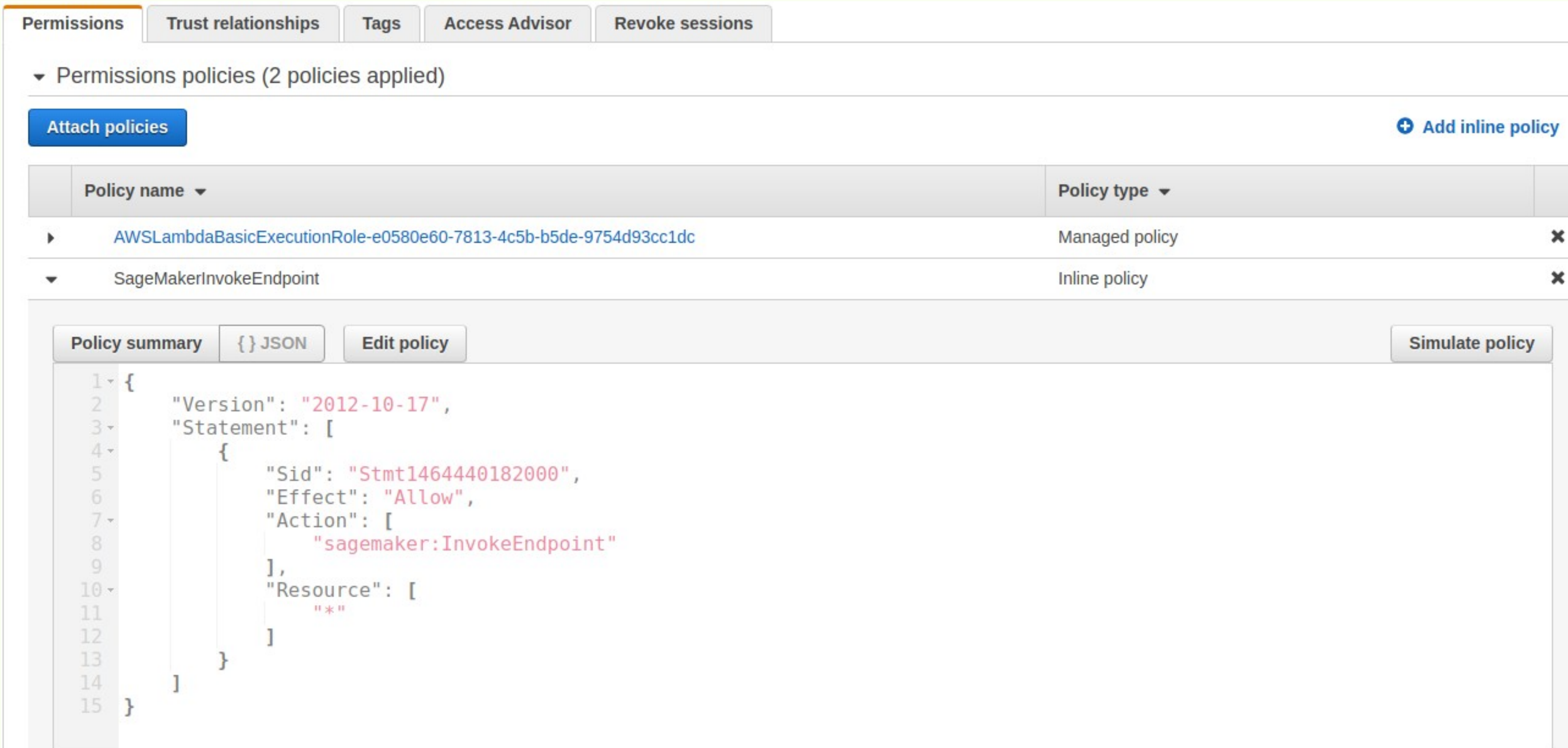

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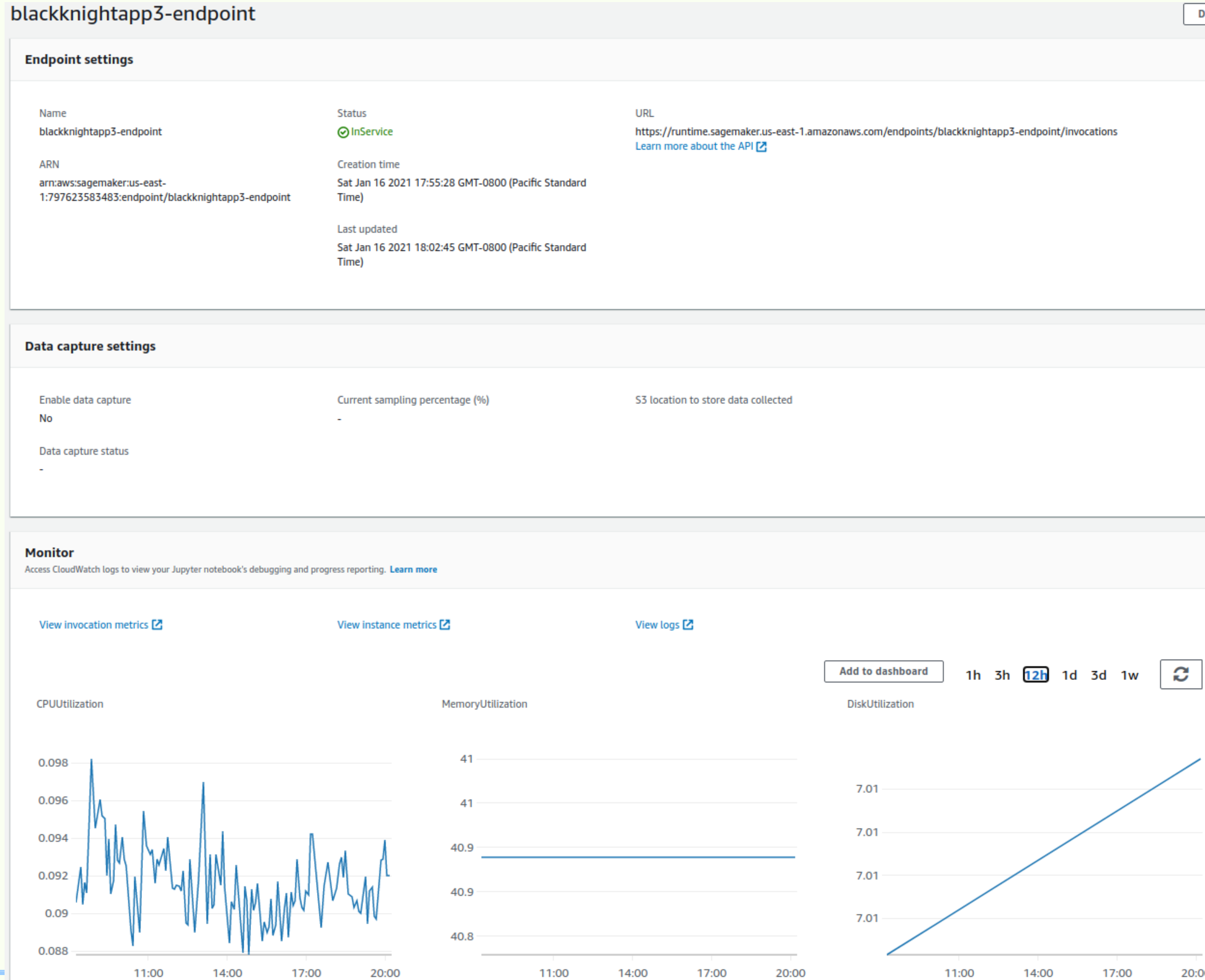

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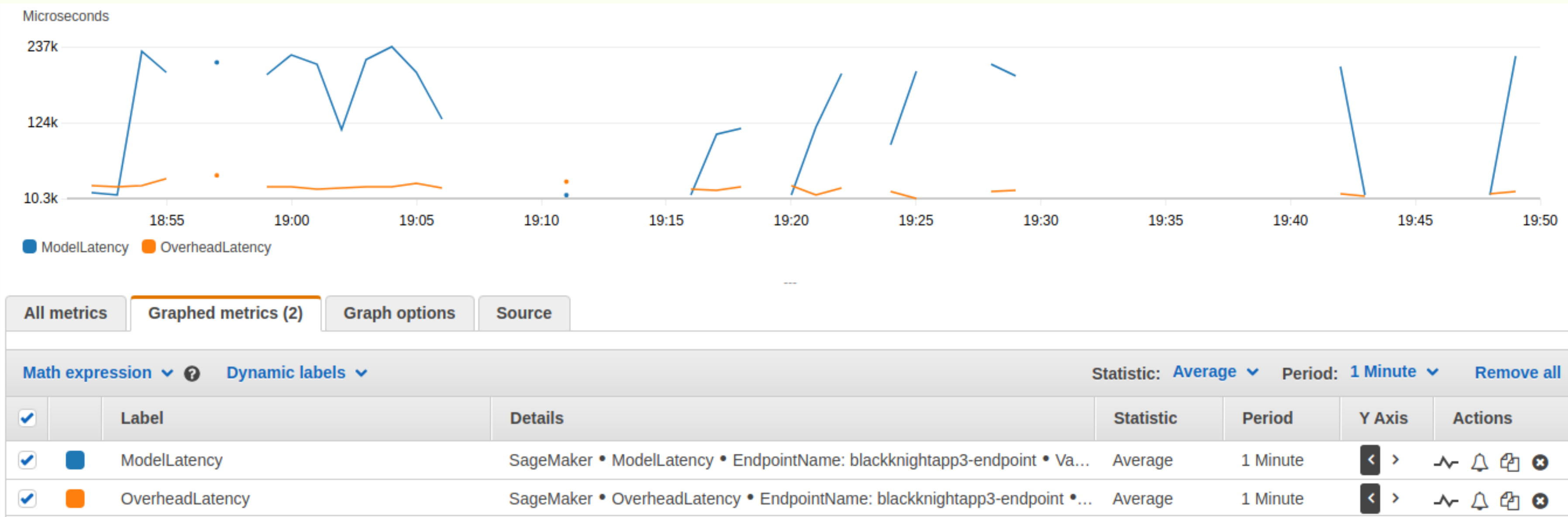
Latencies



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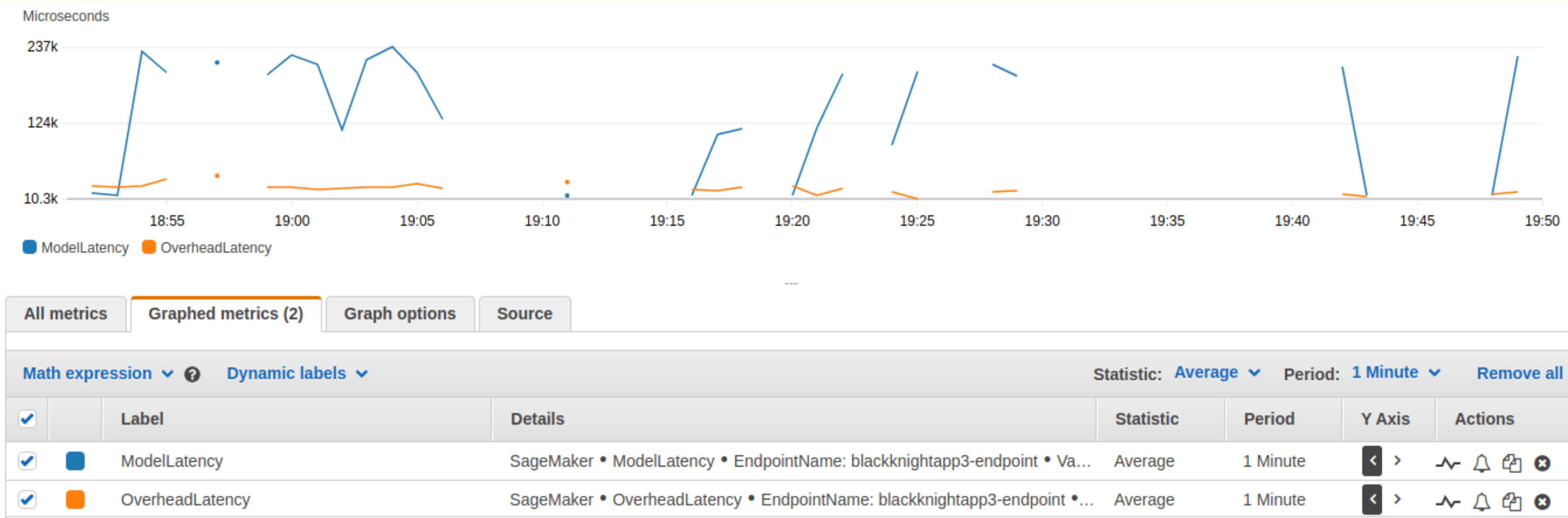

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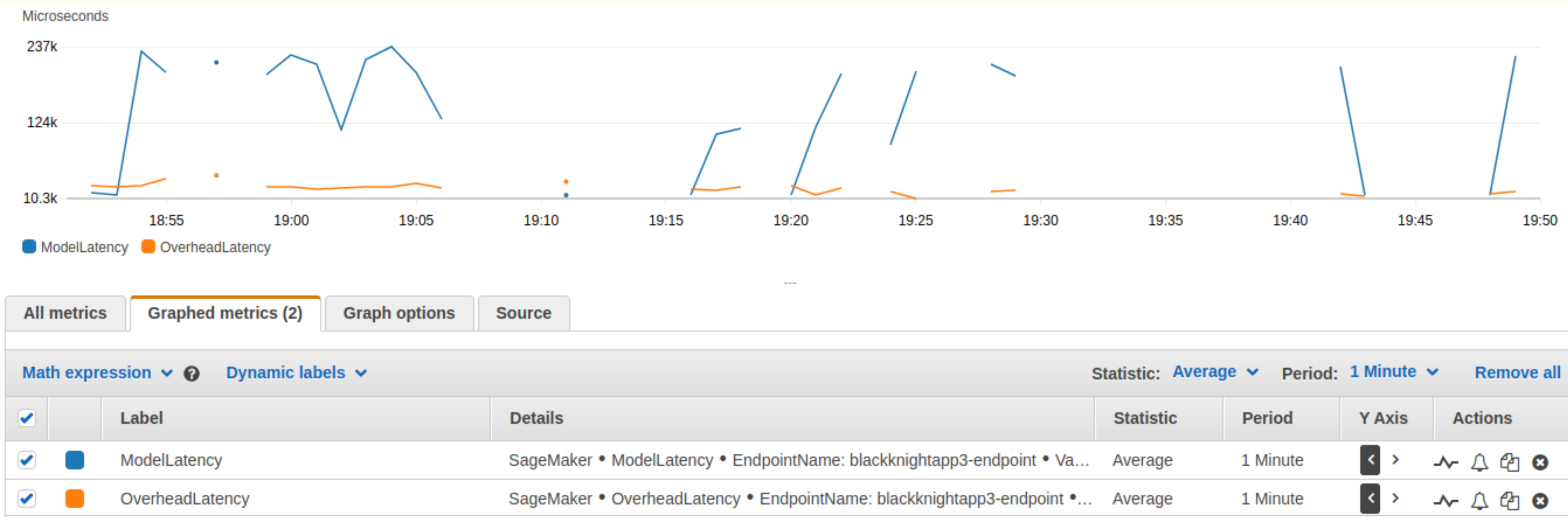

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- (the respective model sizes are 63 M and 273 M, and the TF-IDF vectorizer is 159 M)

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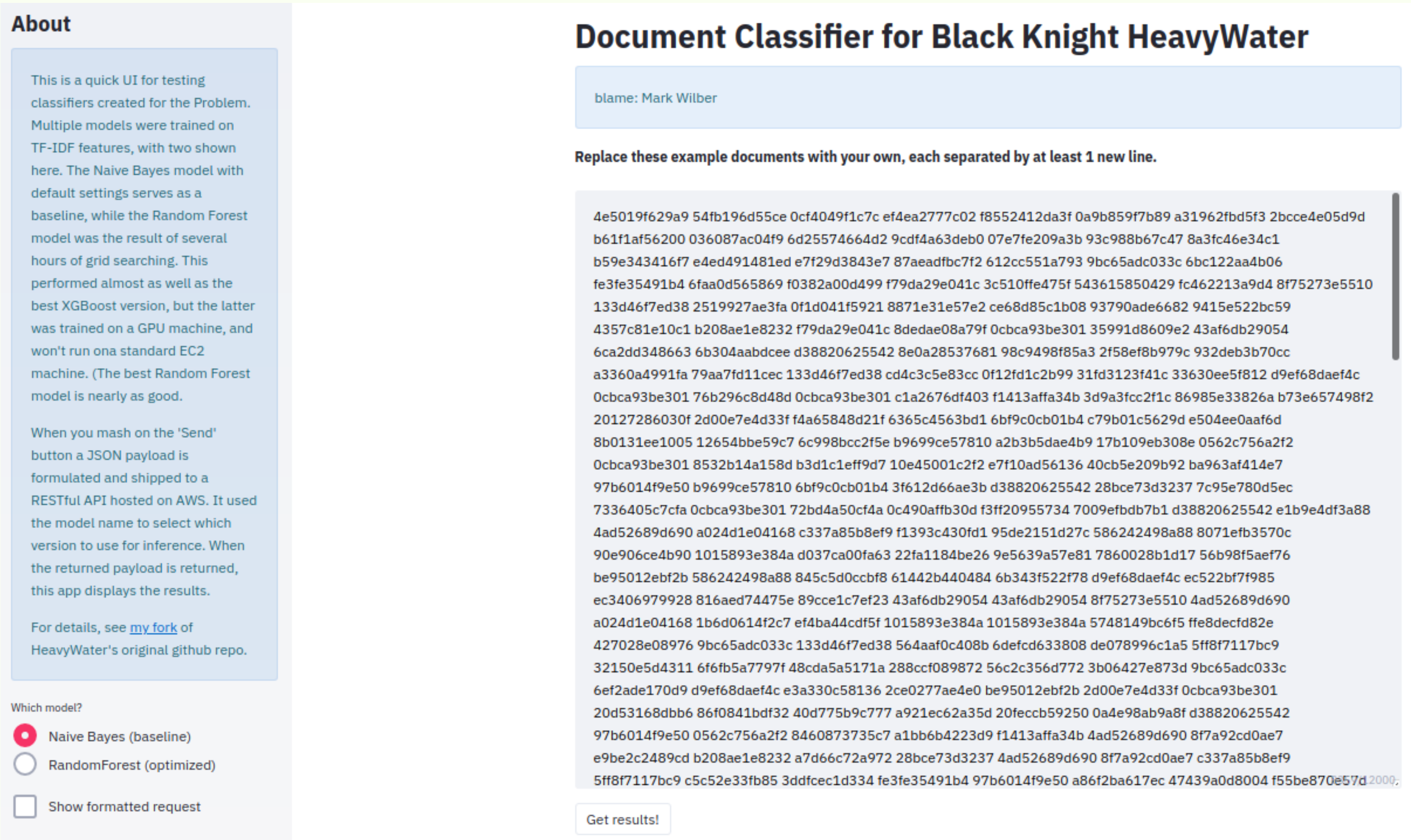

A 15-second demo

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    - sequence-based model (LSTM using sentence embeddings)

That’s all!