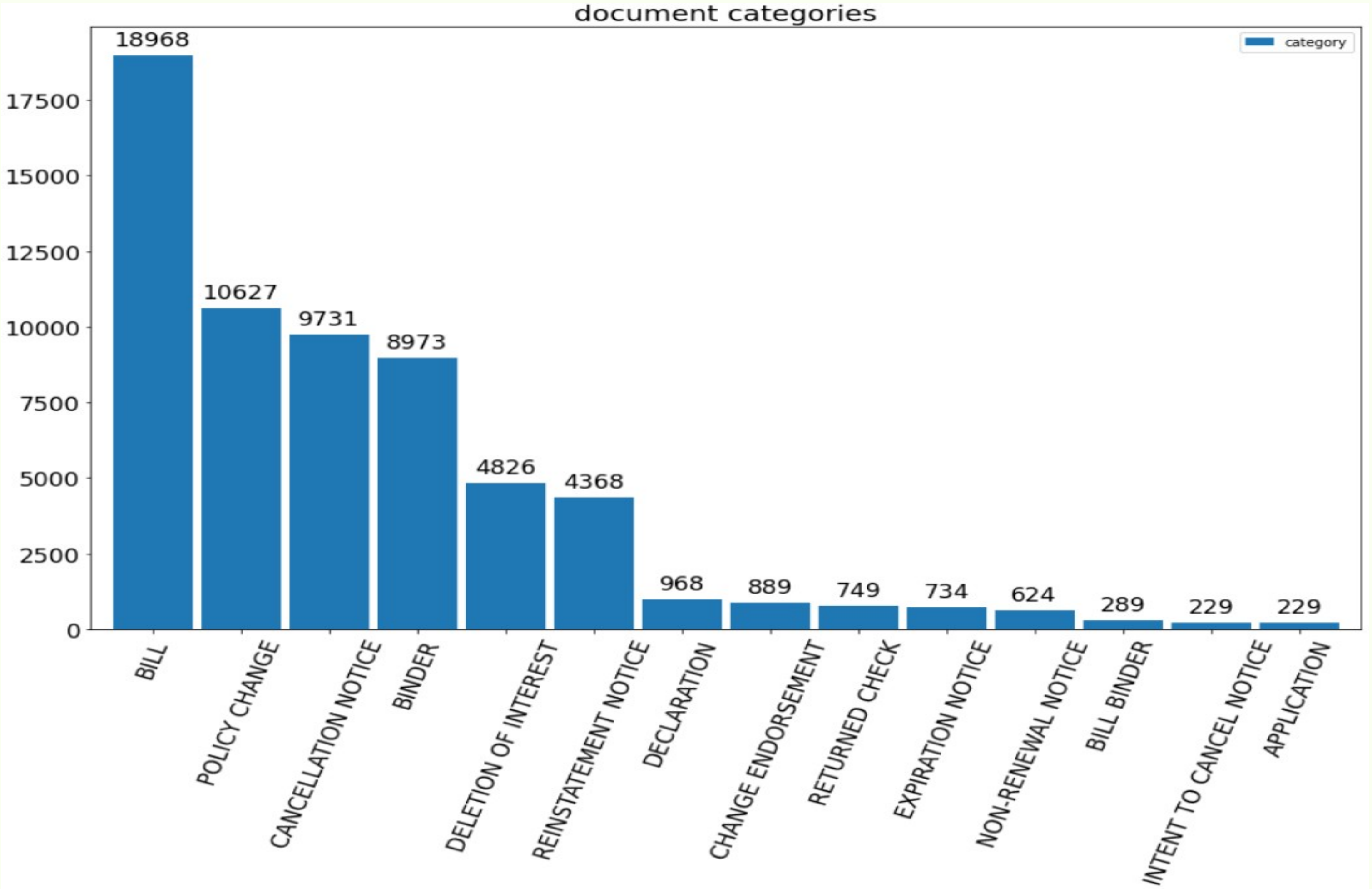
HeavyWater Machine Learning Problem

Solution by Mark Wilber

What we are dealing with

- 62 K documents, 14 categories



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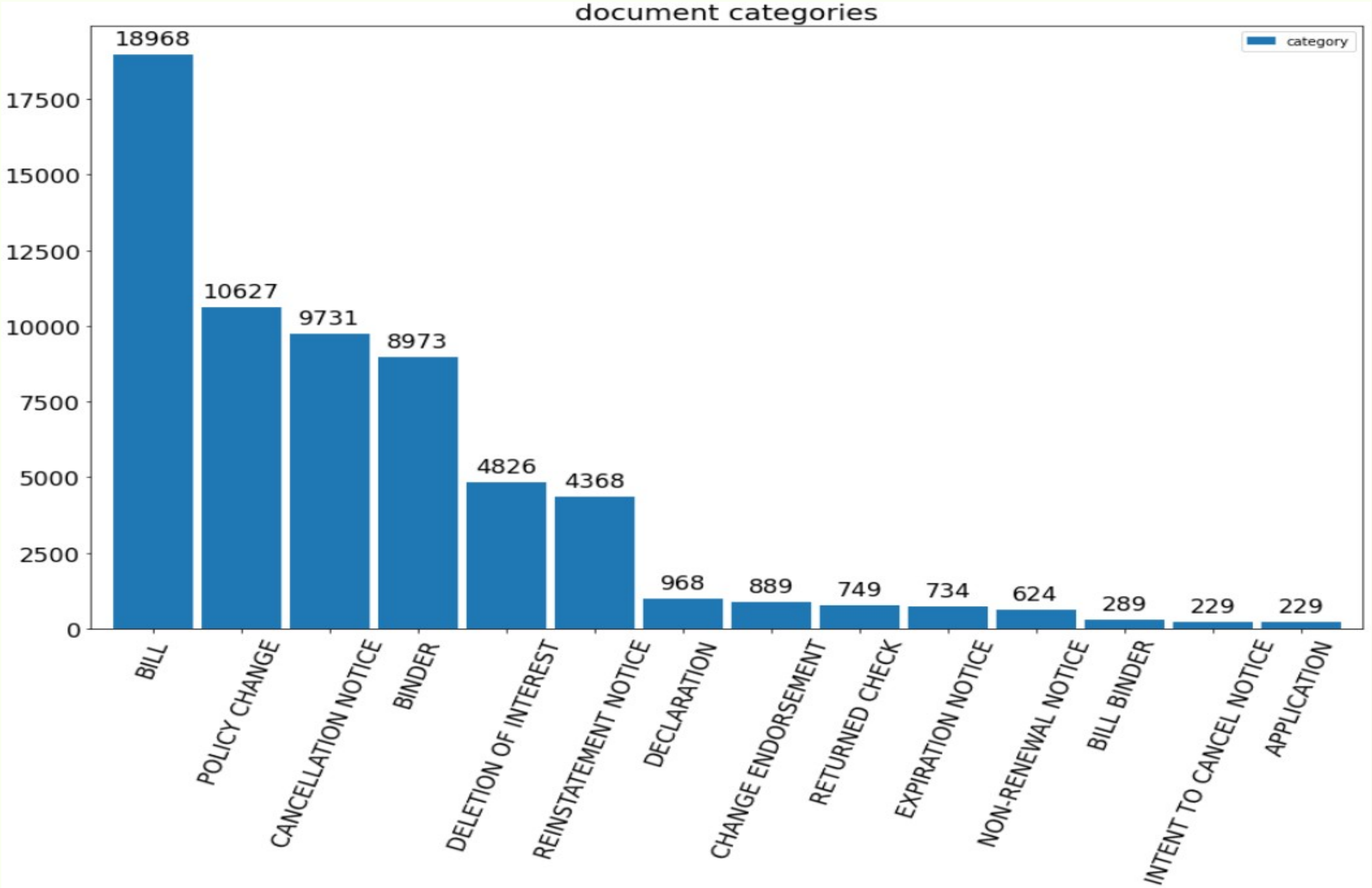
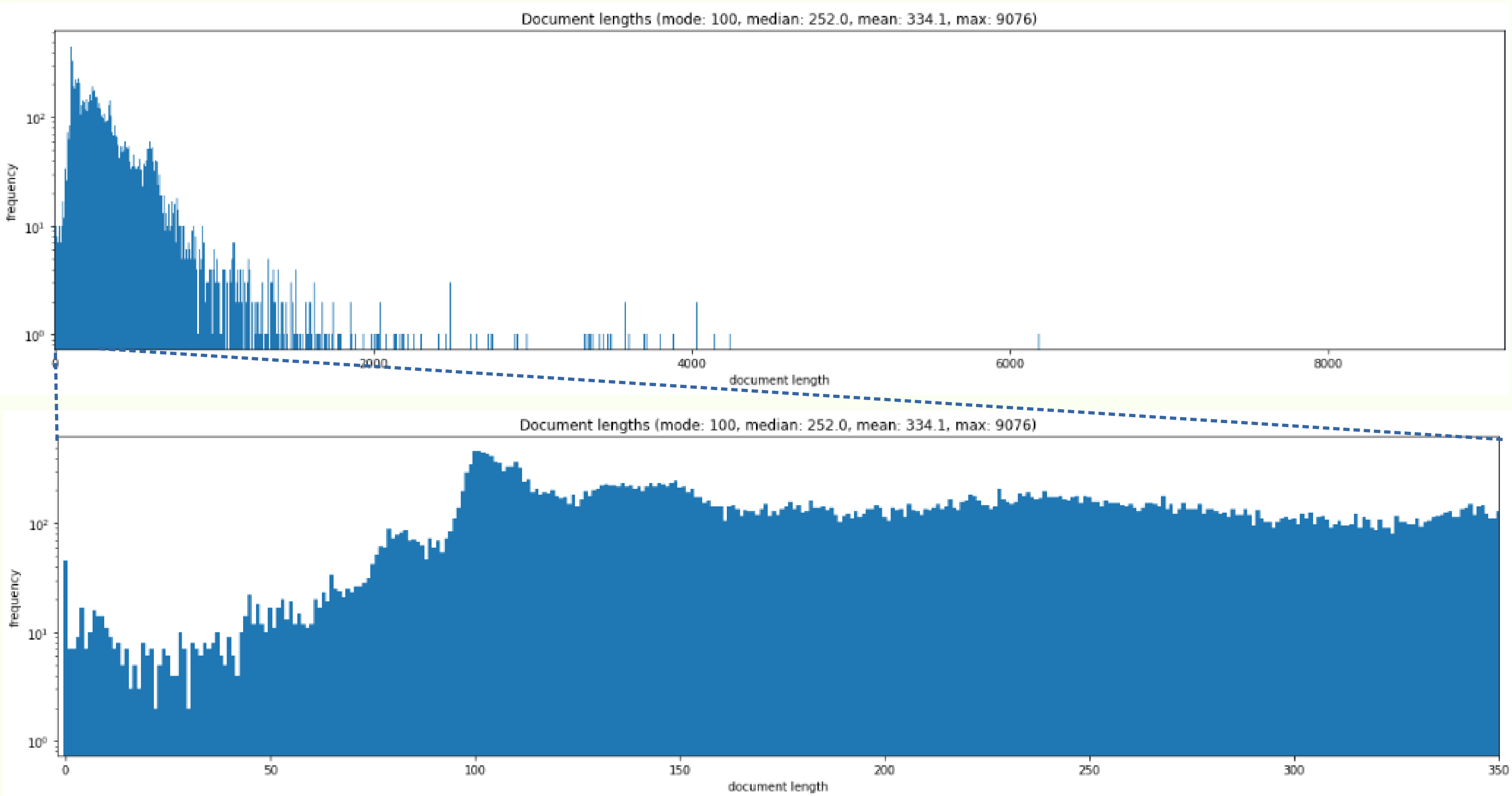
- 62 K documents, 14 categories
- unbalanced classes, spanning nearly 2 orders of magnitude



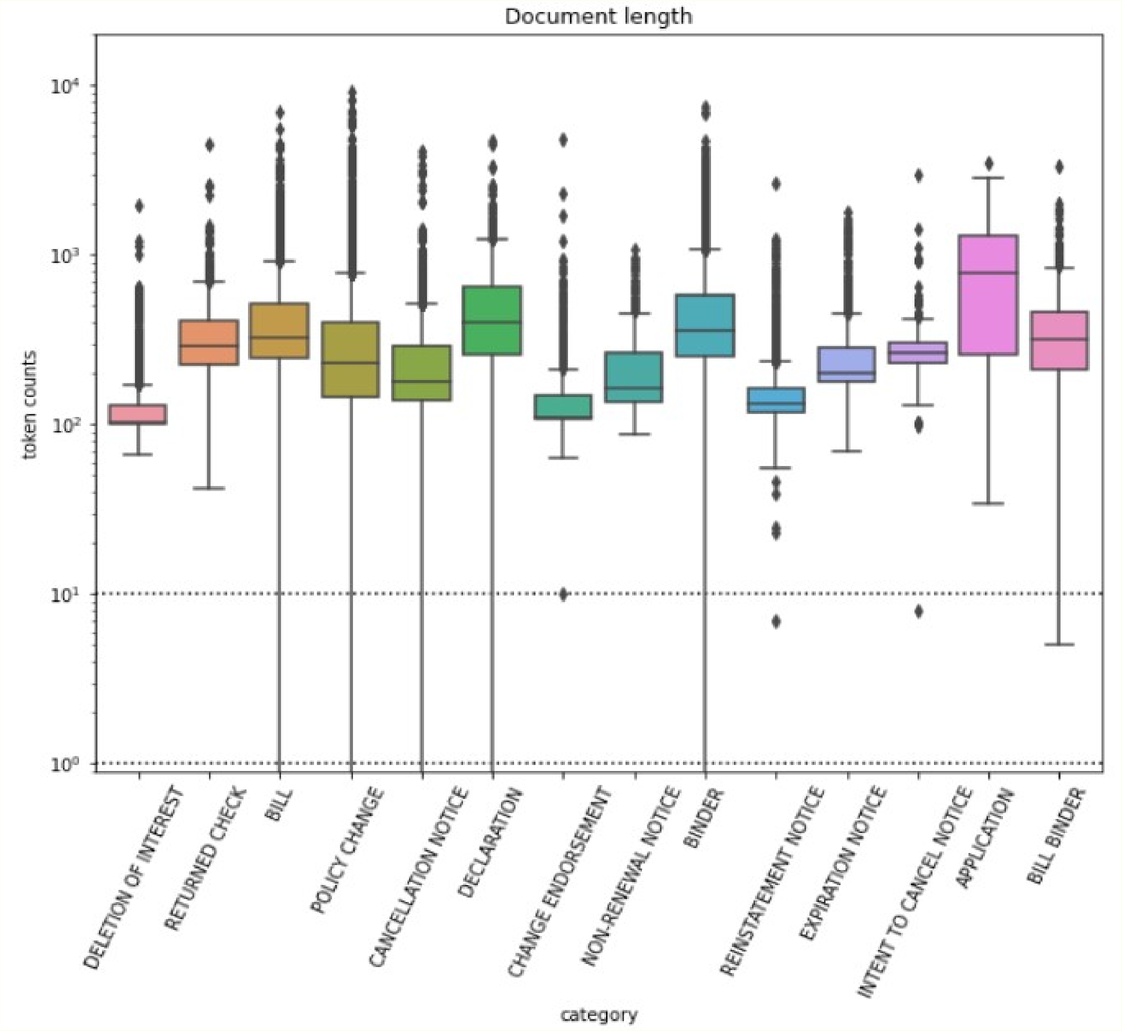
What we are dealing with

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



What we are dealing with

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



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Problem vocabulary exceeds that of OED:

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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

tf	rank	# ≥ rank	frac ≥ rank
6	77189	960745	0.925632
5	88316	949618	0.914912
4	103088	934846	0.900680
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- explanation: most of the tokens are "uninformative" (garbage)

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

⇨ smudges create nonsense terms

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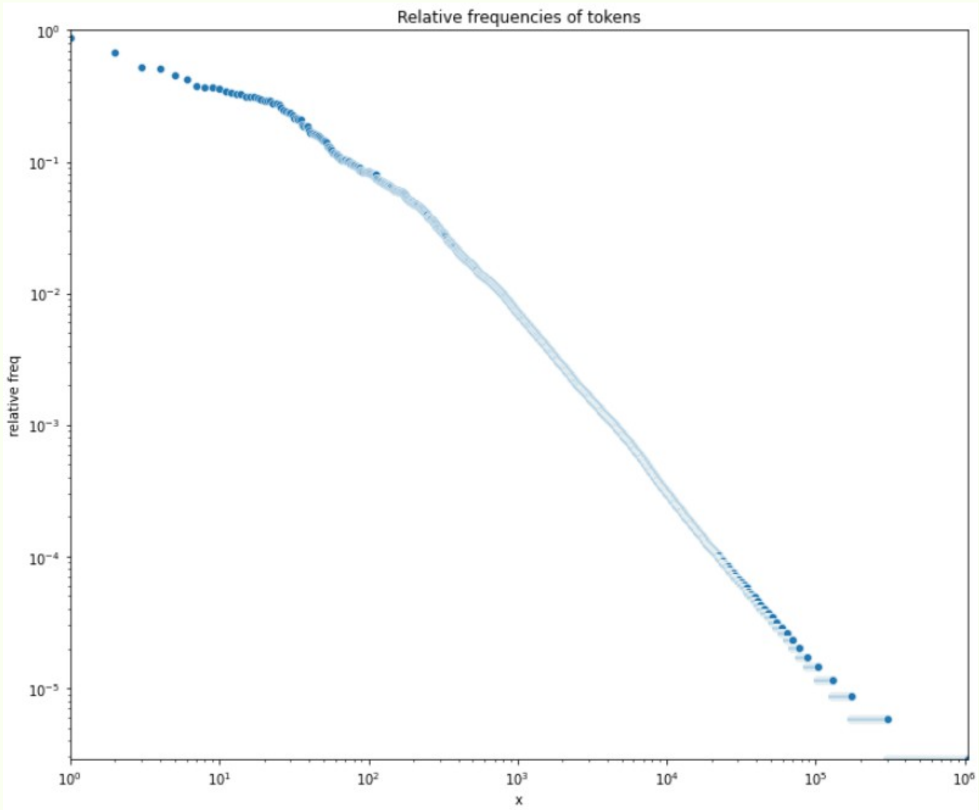
- Most frequent terms don't follow Zipf's relation



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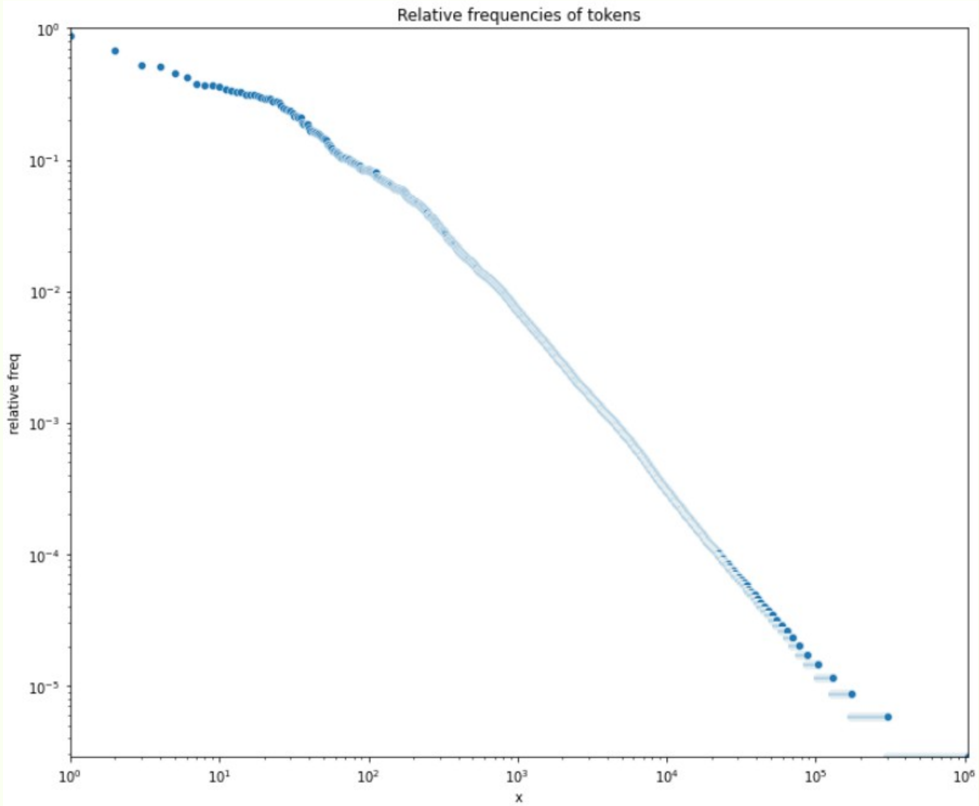

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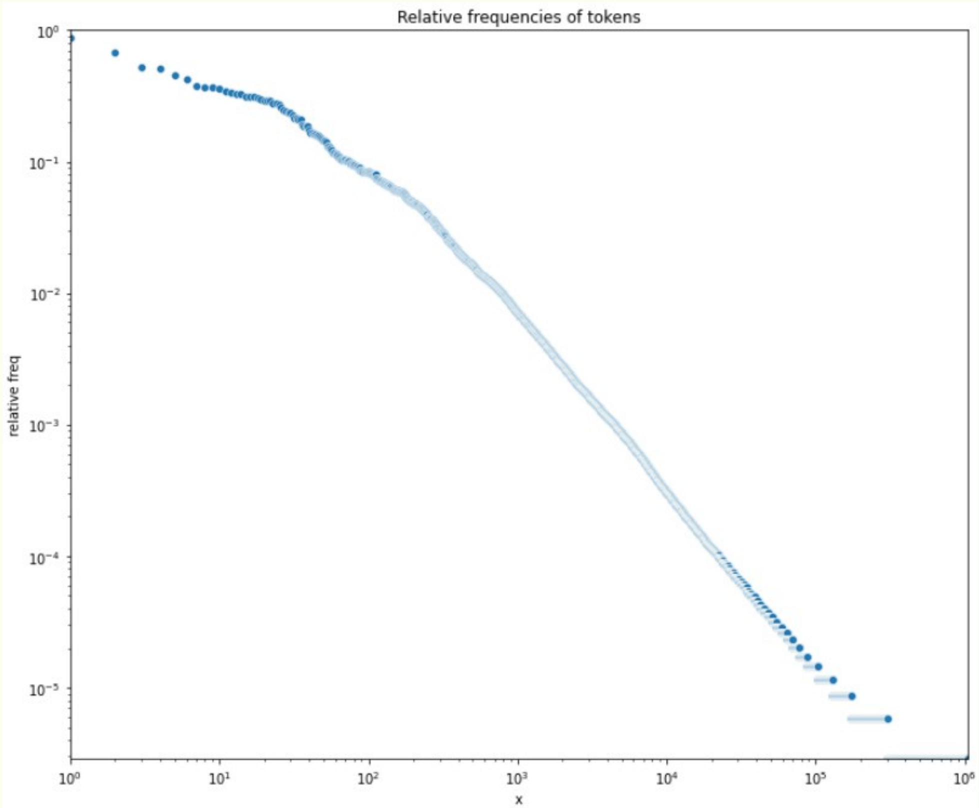

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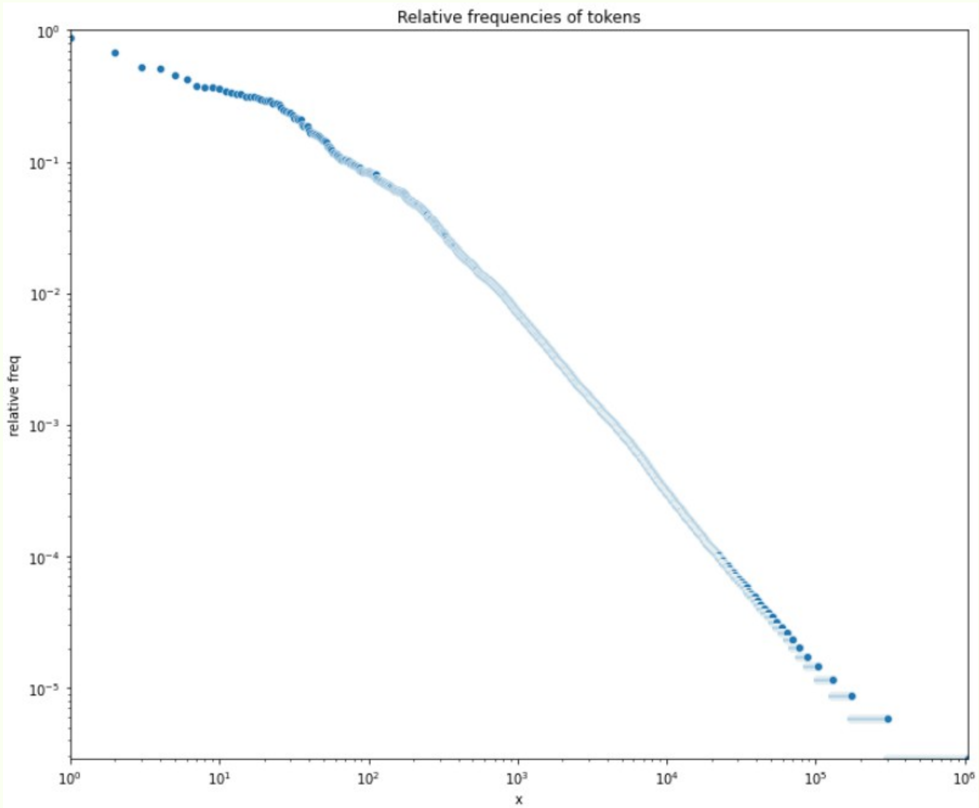

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⇨ *this corpus seems to be unusual ...*

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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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- default settings for baseline
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- best with `alpha=0.0139 and norm=False` yielded substantial improvements

    ⇨ model *3 × larger*

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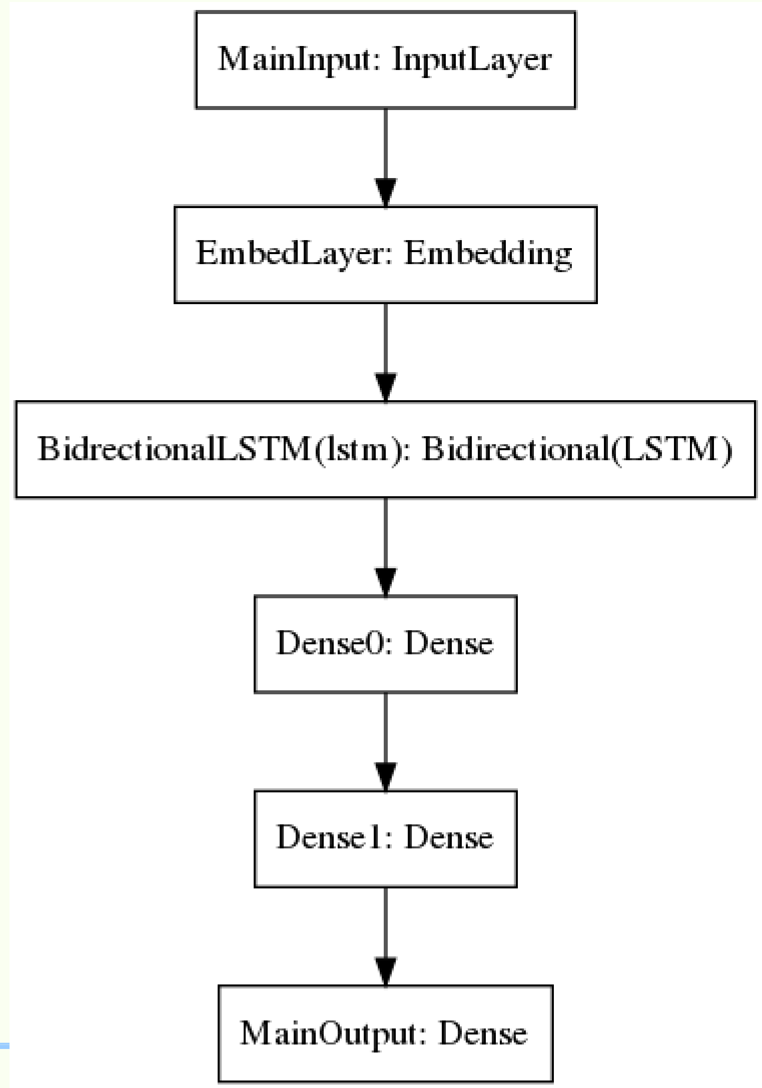
Modeling

LSTM

- Sequence lengths {64, 128, 256, 512)
- `maxVocabCt` {100000, 200000}
- regularizaton: `dropout=0.15`, `recurrent_dropout=0.40`
- Shorter sequences better



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LSTM + `docLength`

- auxiliary feature for document length
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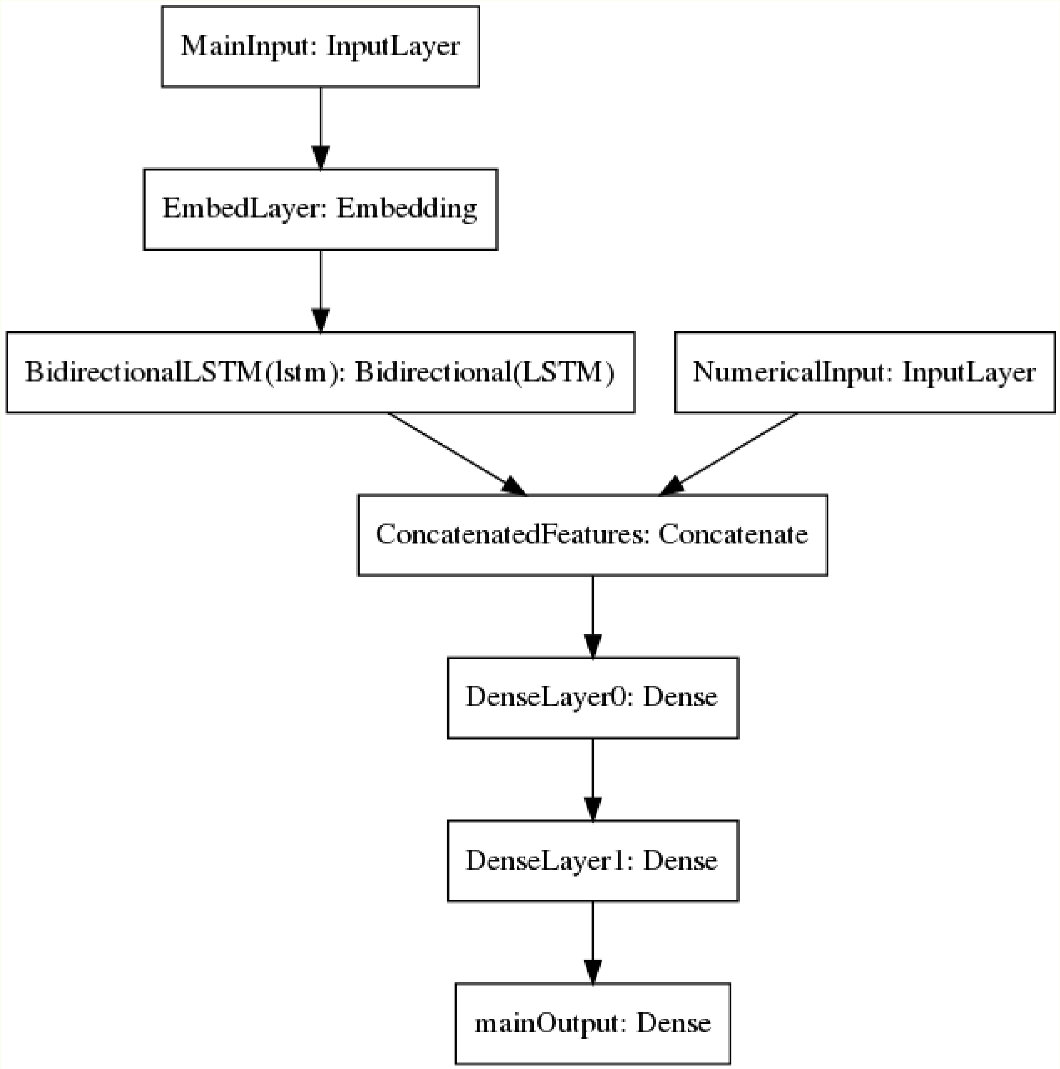

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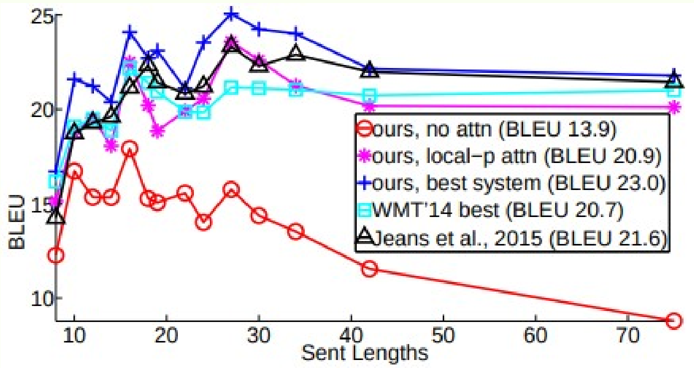
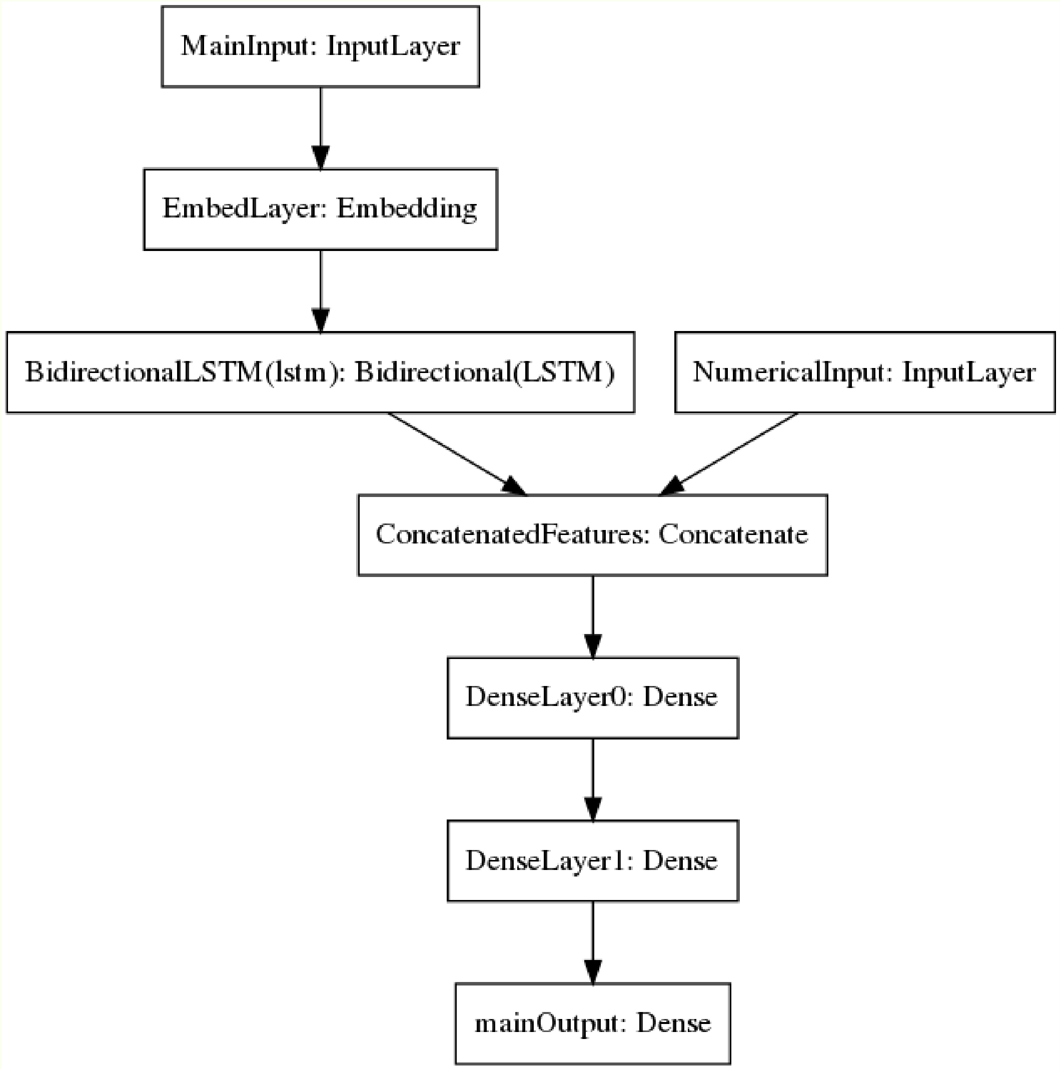


Figure 6: **Length Analysis** – translation qualities of different systems as sentences become longer.

Luong, M-T, et al [arXiv 1508.04025v5, 2015]



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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
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

- reminder: macro averaged ⇨ straight average of scores for each class
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- Random Forest and XGBoost “identical” good results

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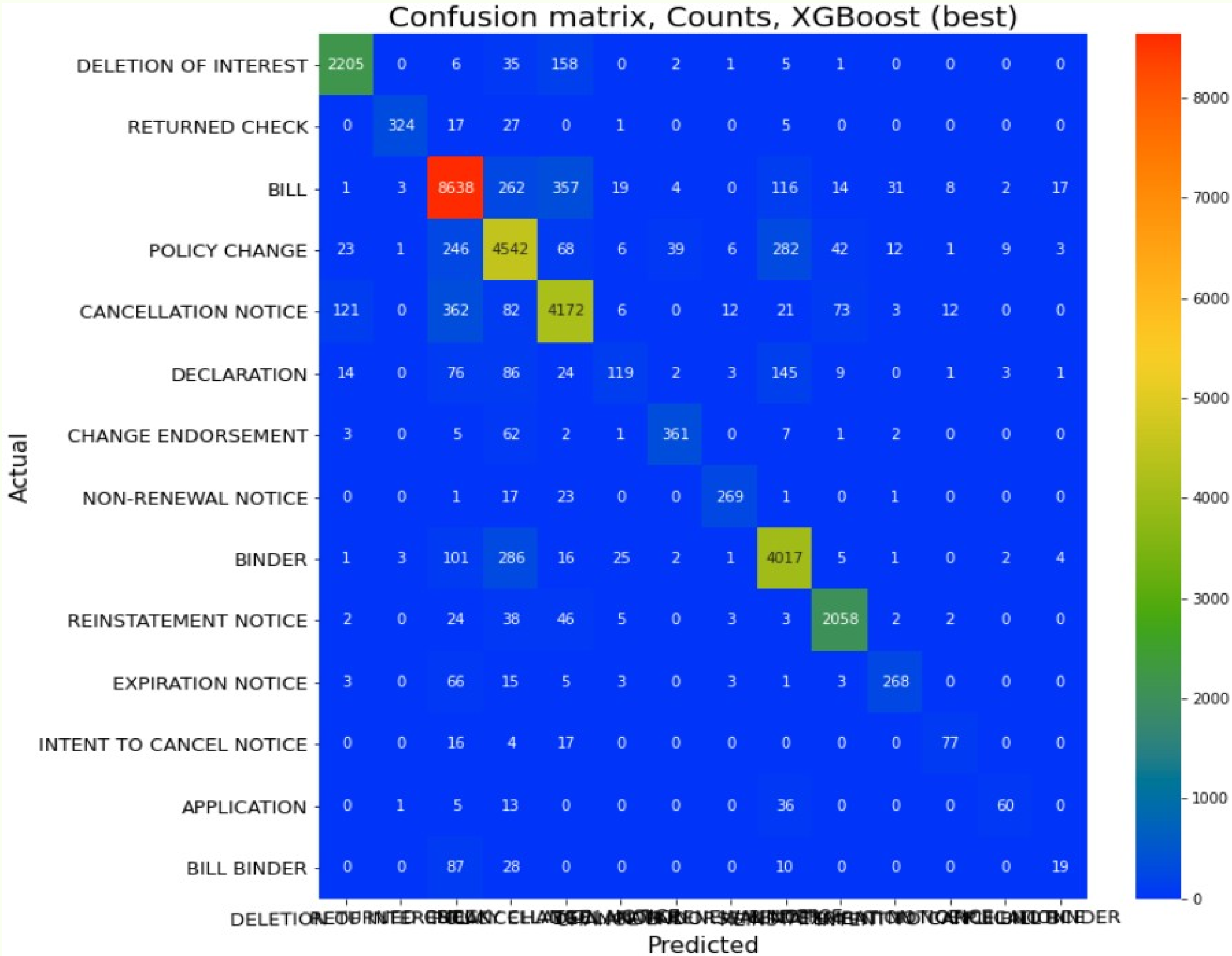
Gradient Boosting default	0.81	0.64	0.69	0.81	0.81	0.80	1.2
XGBoost default	0.79	0.65	0.70	0.82	0.82	0.82	5.4
XGBoost best	0.82	0.73	$\boxed{0.76}$	0.87	0.87	$\boxed{0.87}$	21
Bidirectional LSTM	0.54	0.58	0.54	0.76	0.70	0.72	53
Bidirectional LSTM	0.50	0.61	0.52	0.78	0.69	0.73	202

- reminder: macro averaged ⇨ straight average of scores for each class
  weighted average ⇨ average of all class scores weighted by support
- if need good scores for smaller classes, focus on macro averages
- if overall results most important, focus on weighted averages

- Random Forest and XGBoost “identical” good results
- Caution: errors in small classes $\mathcal{O}$(10%) ⇨ impact macro averages most

Model Results



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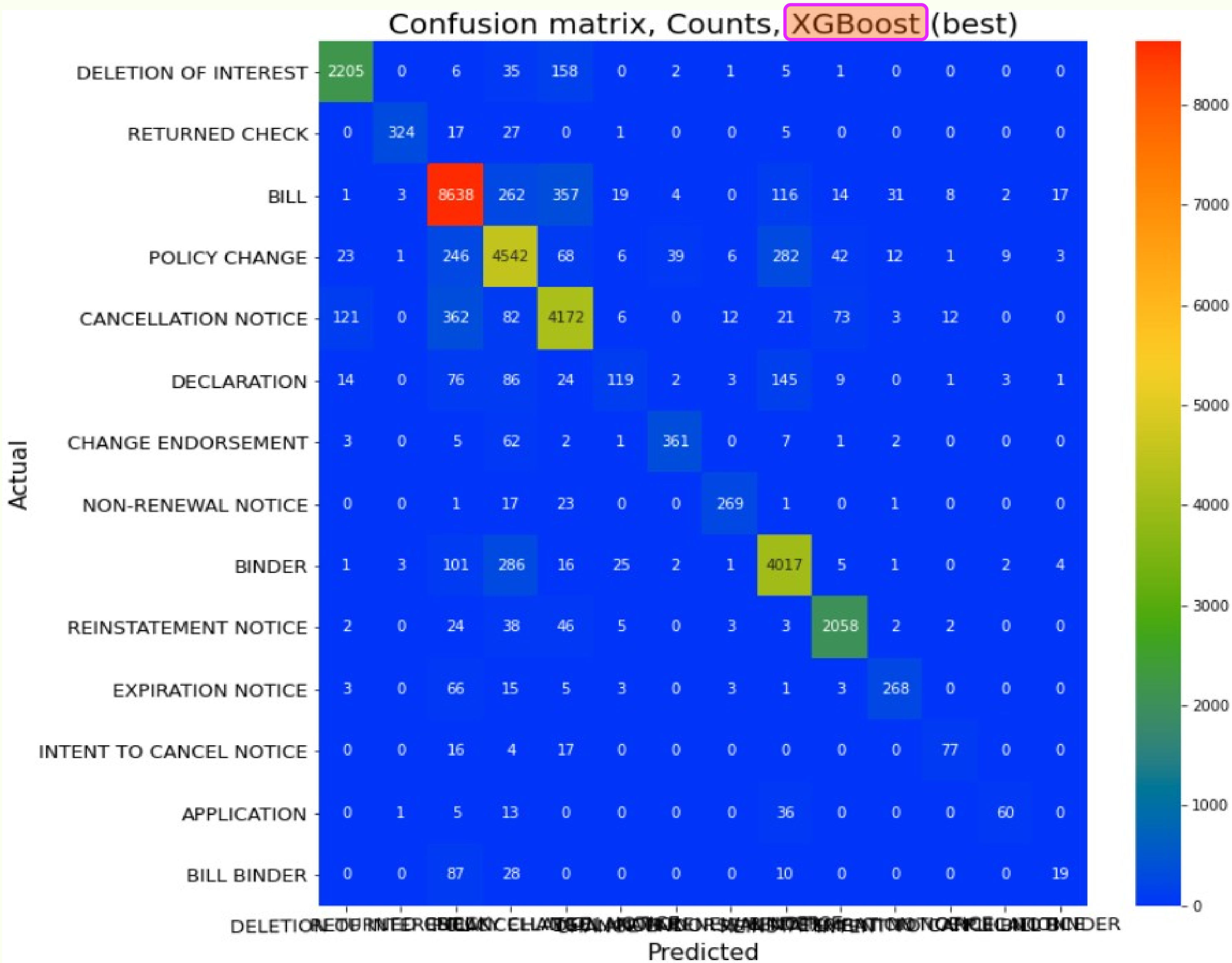

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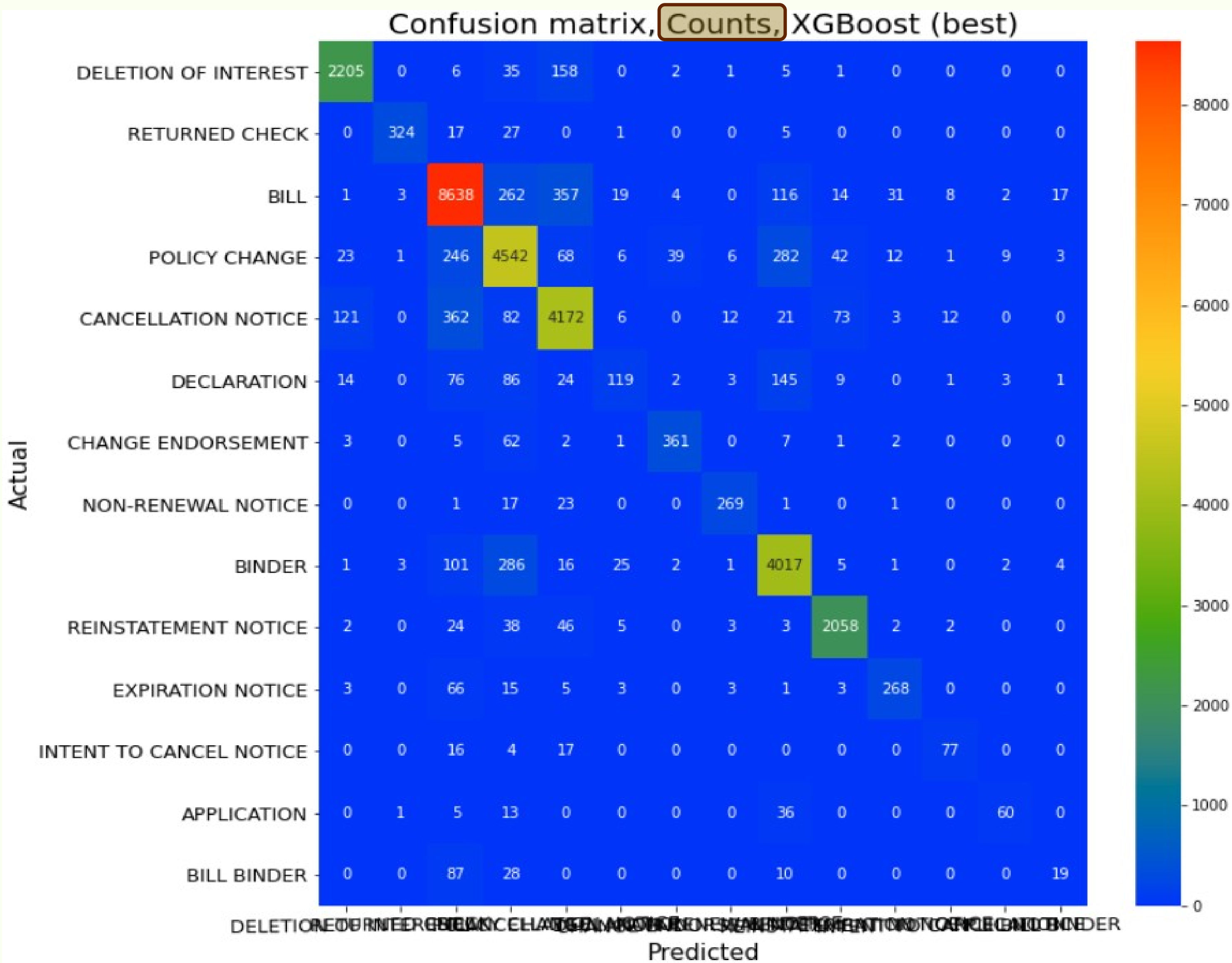

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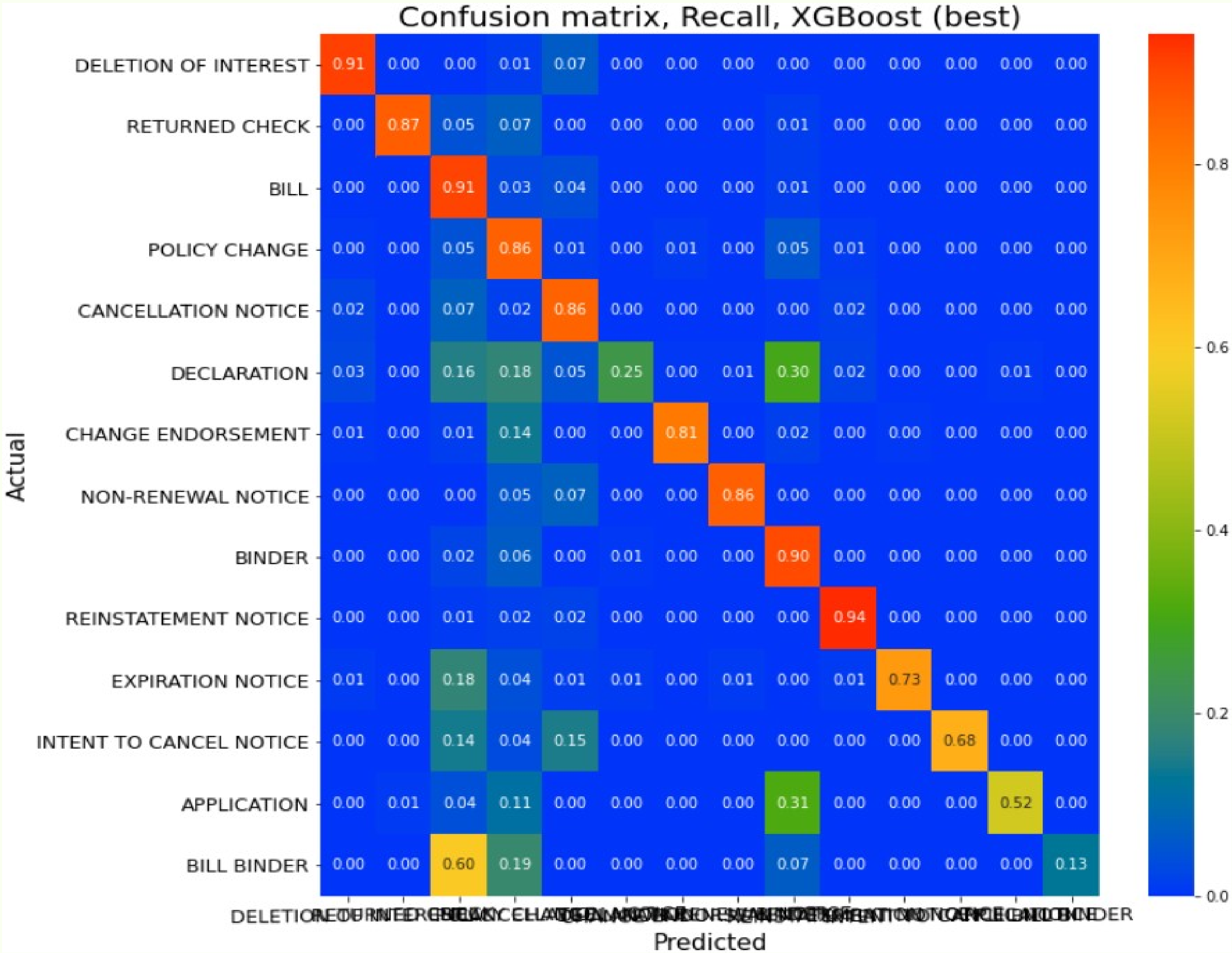

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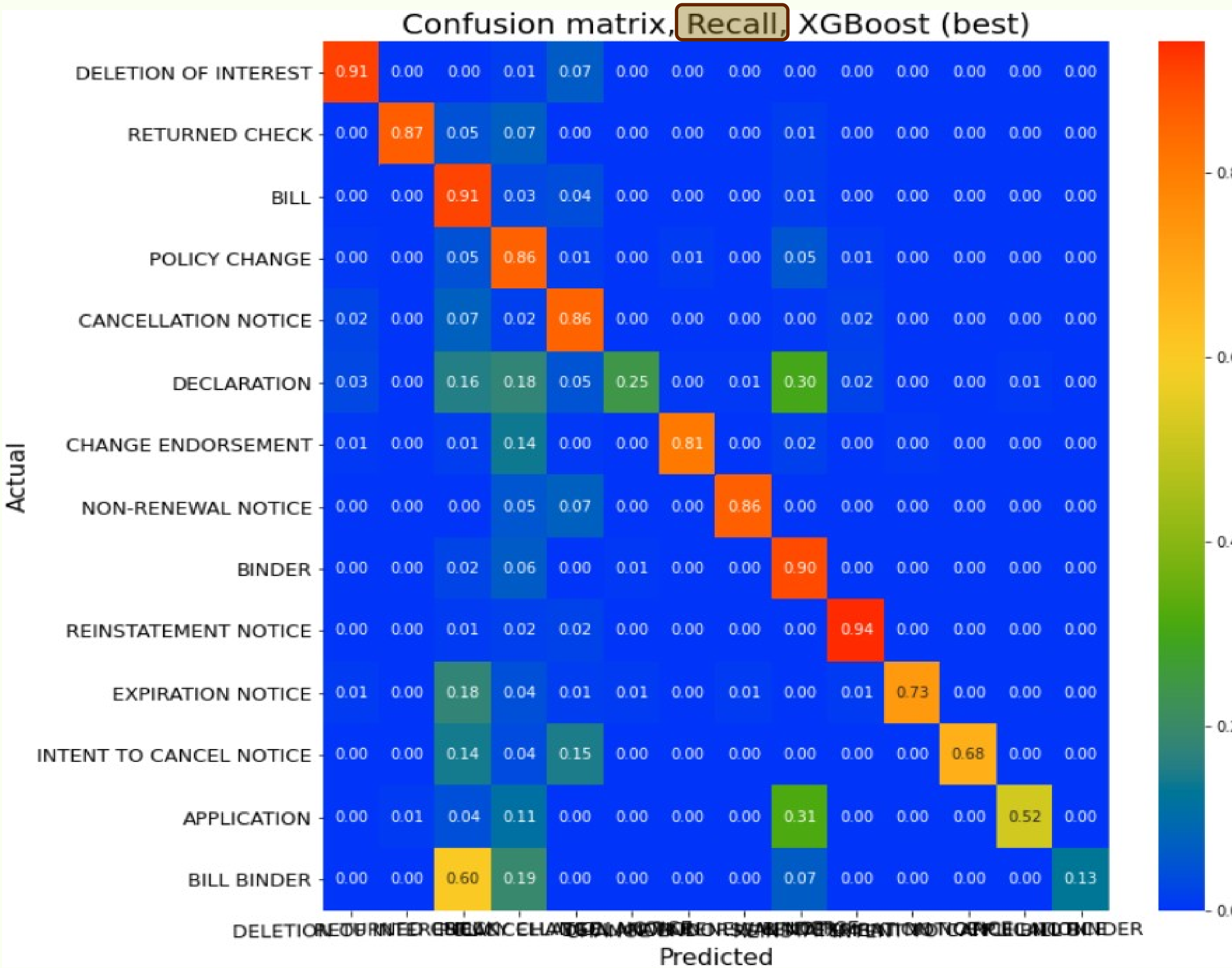

$$R = \frac{TP}{TP + FN}$$

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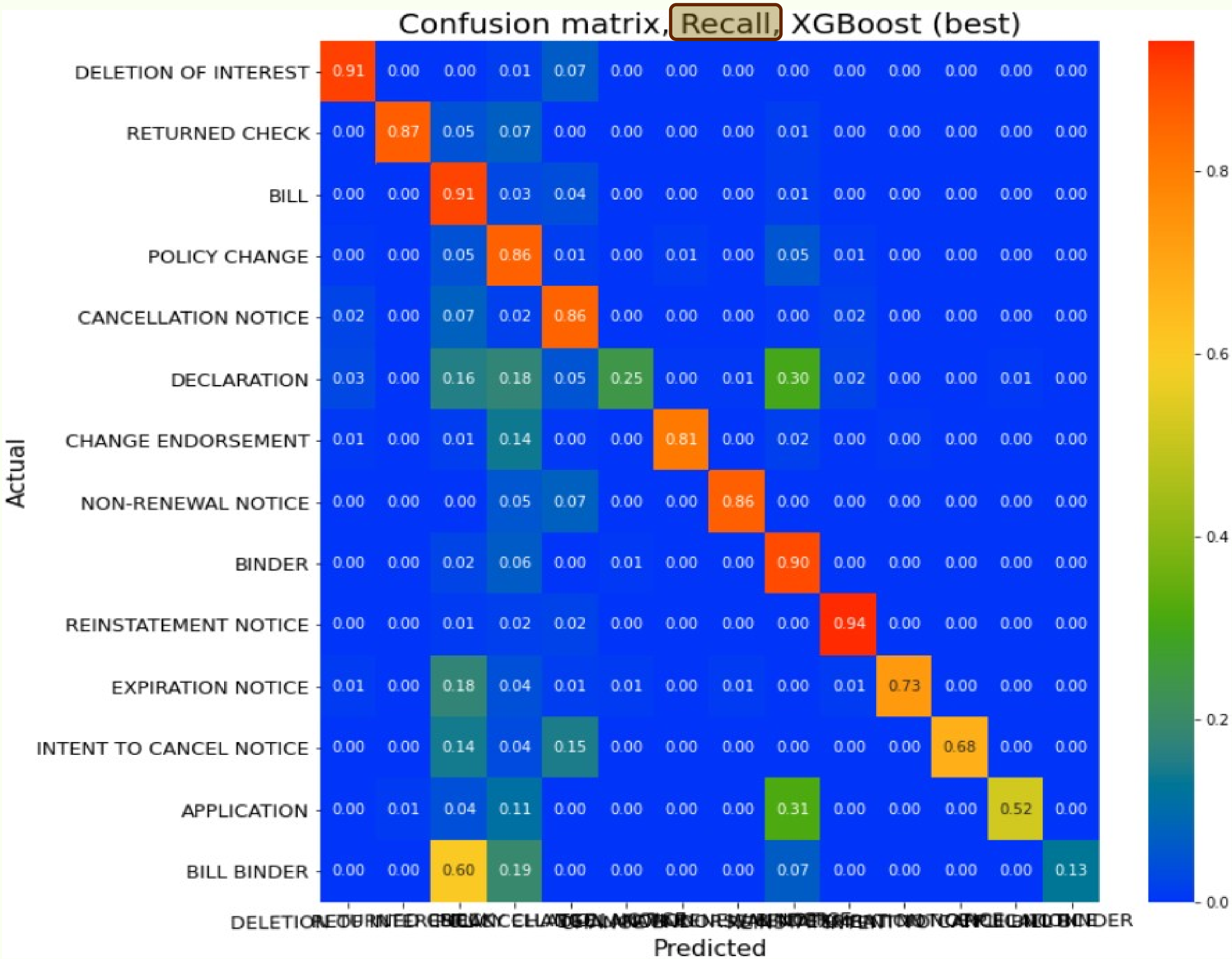

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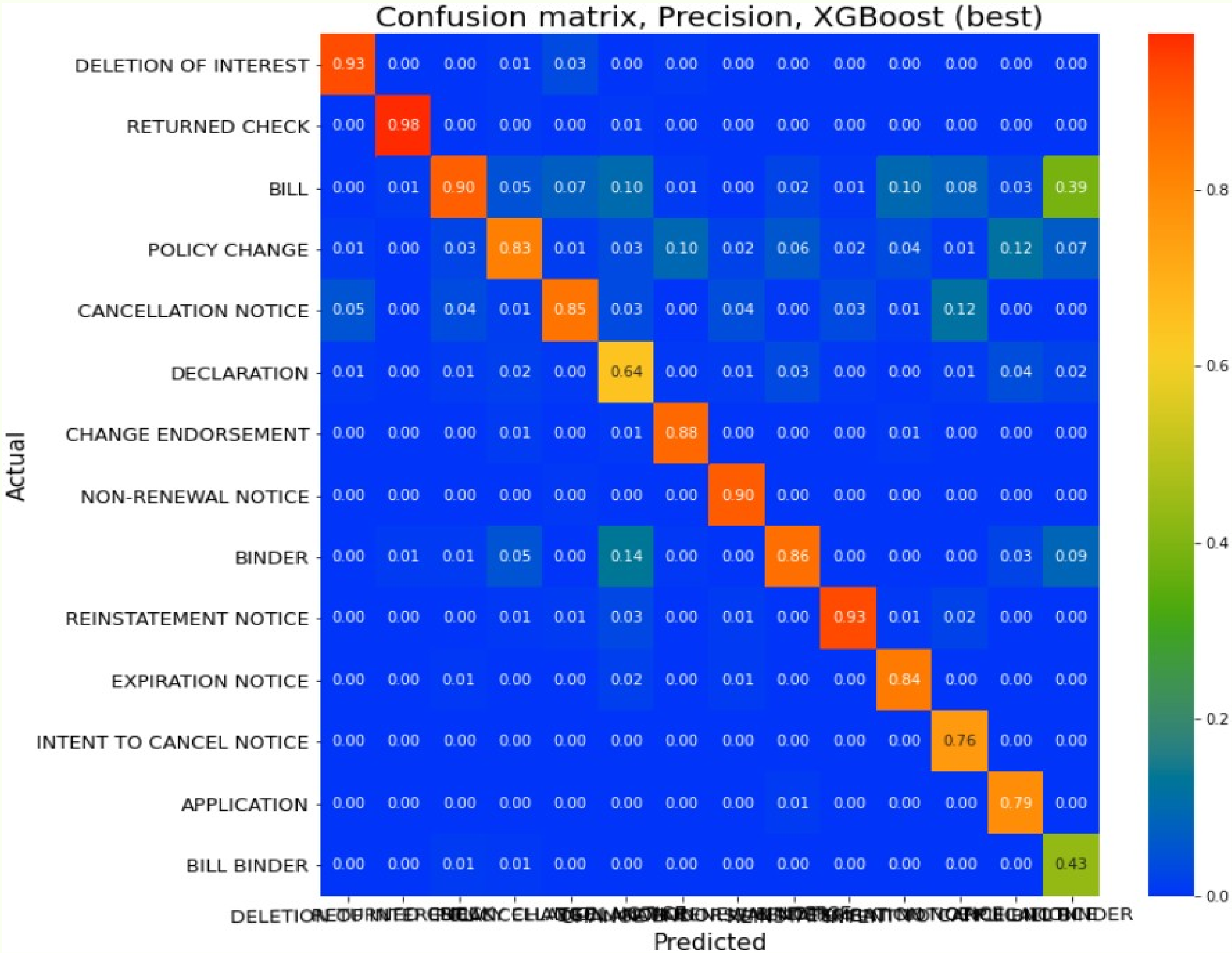

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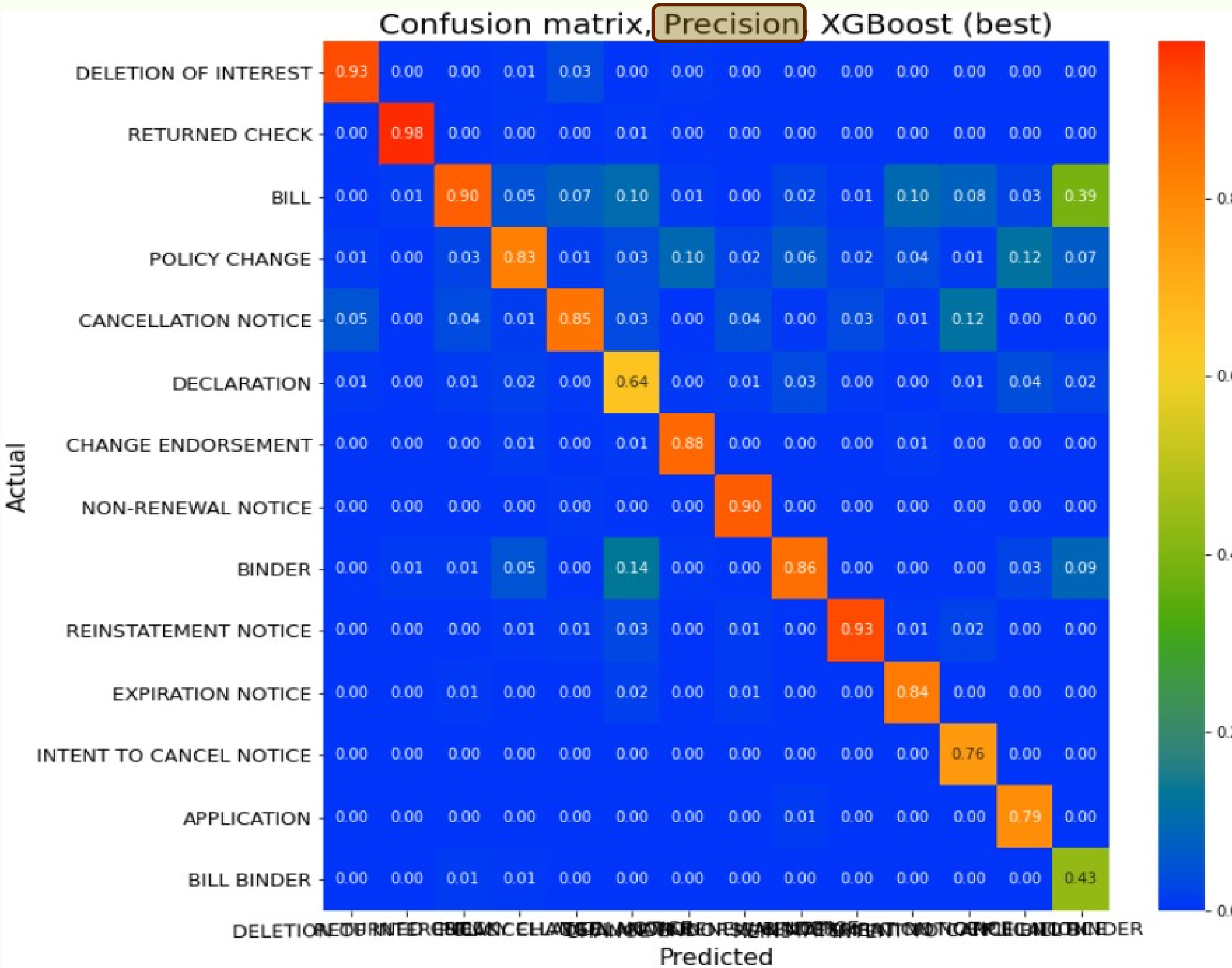

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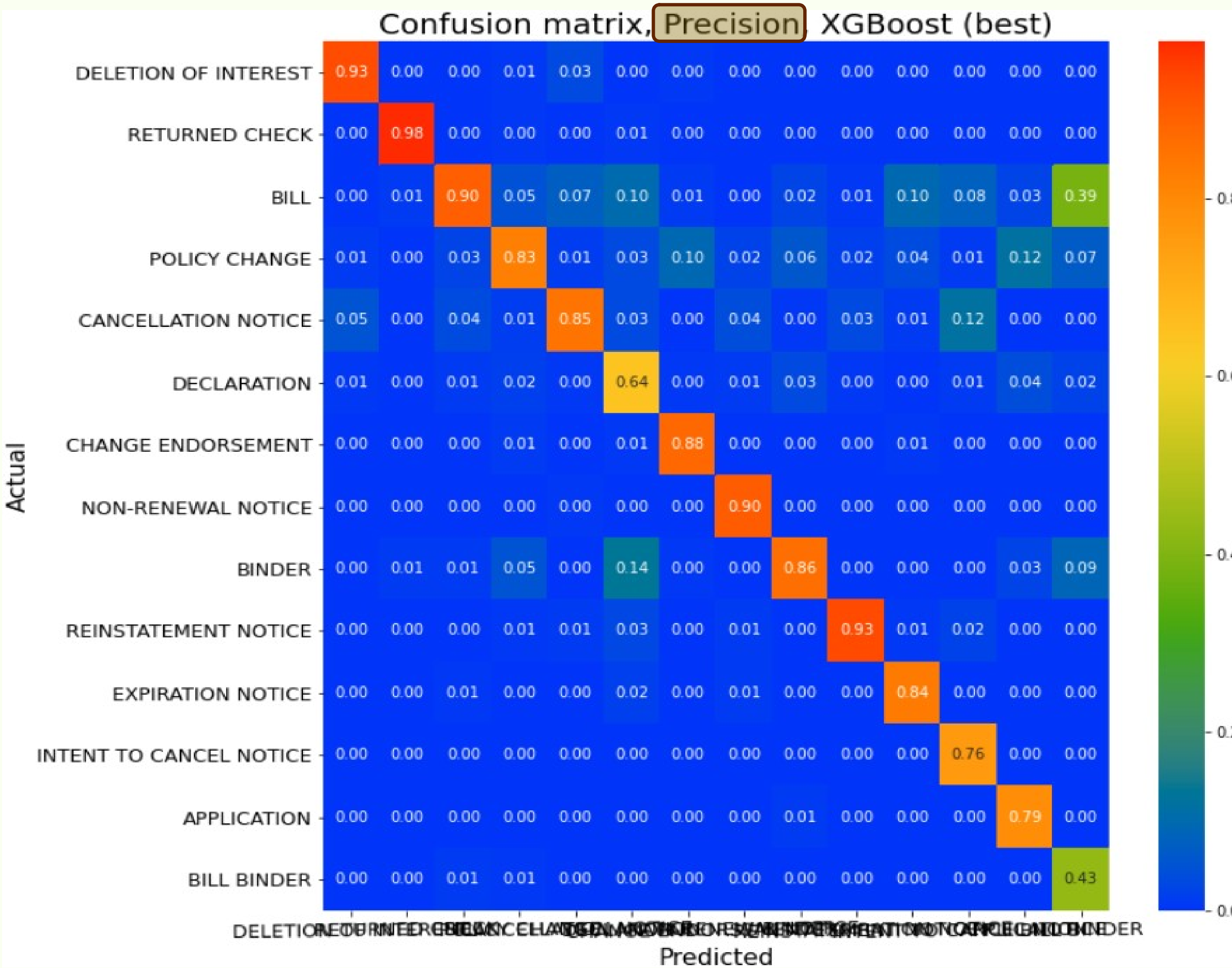

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Deployed Solution

General notes

- Find code in github repo

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- image size 912 MB

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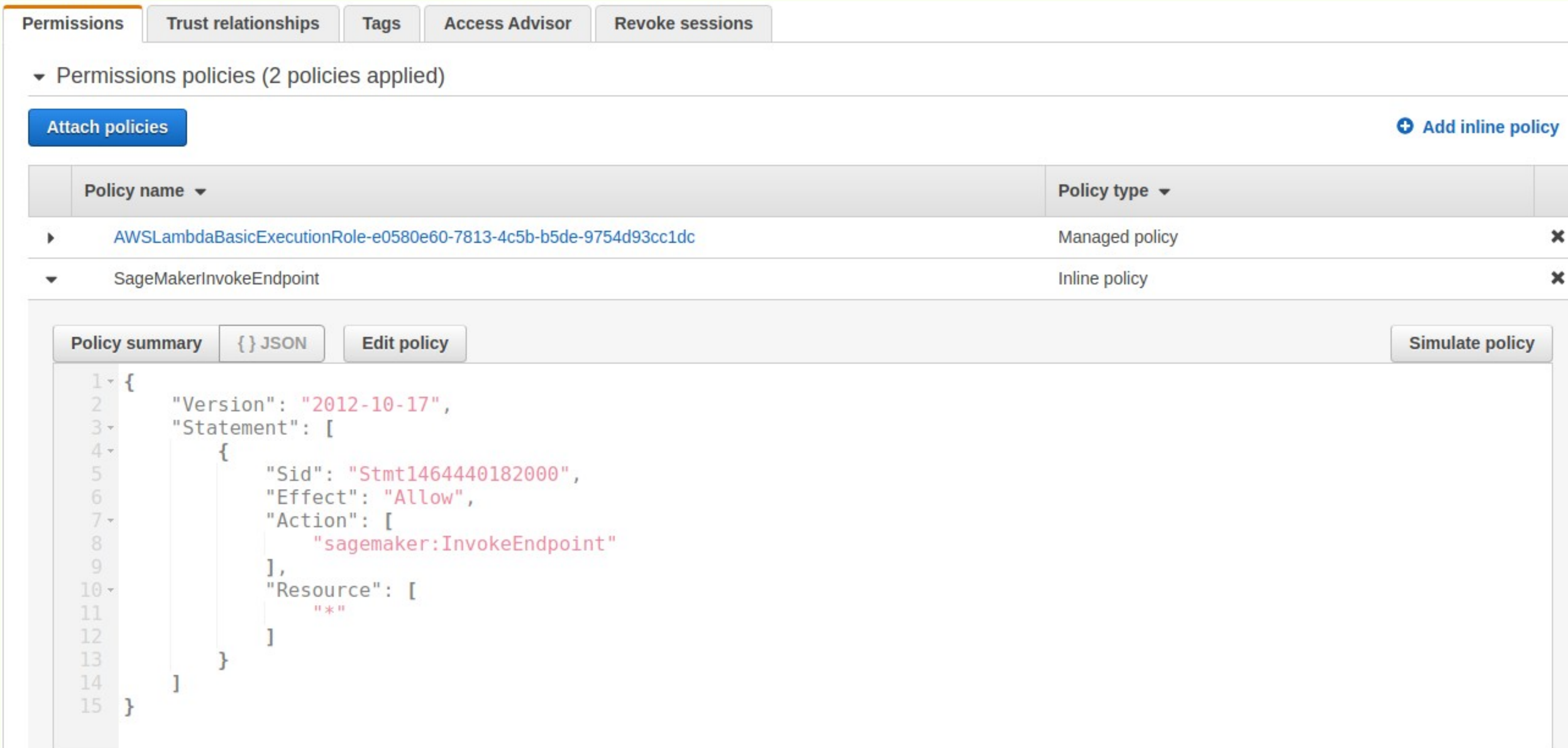

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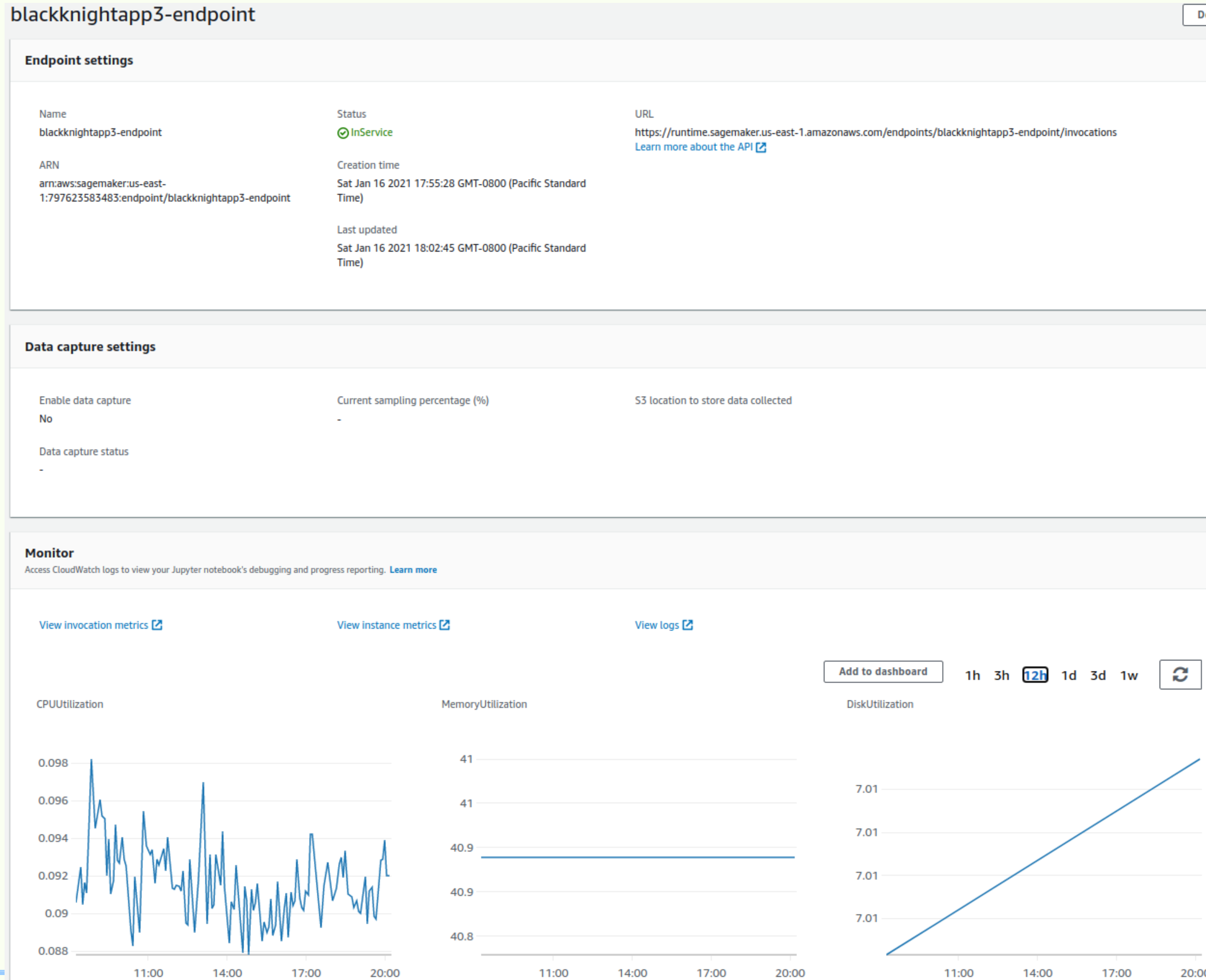

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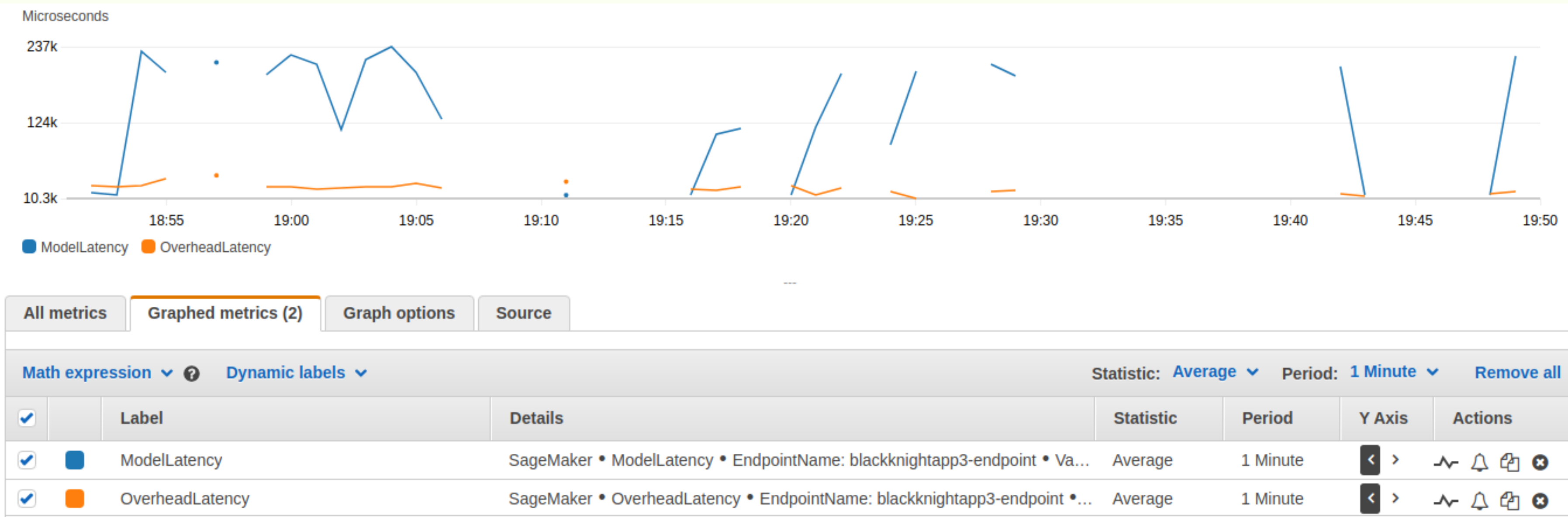
Latencies



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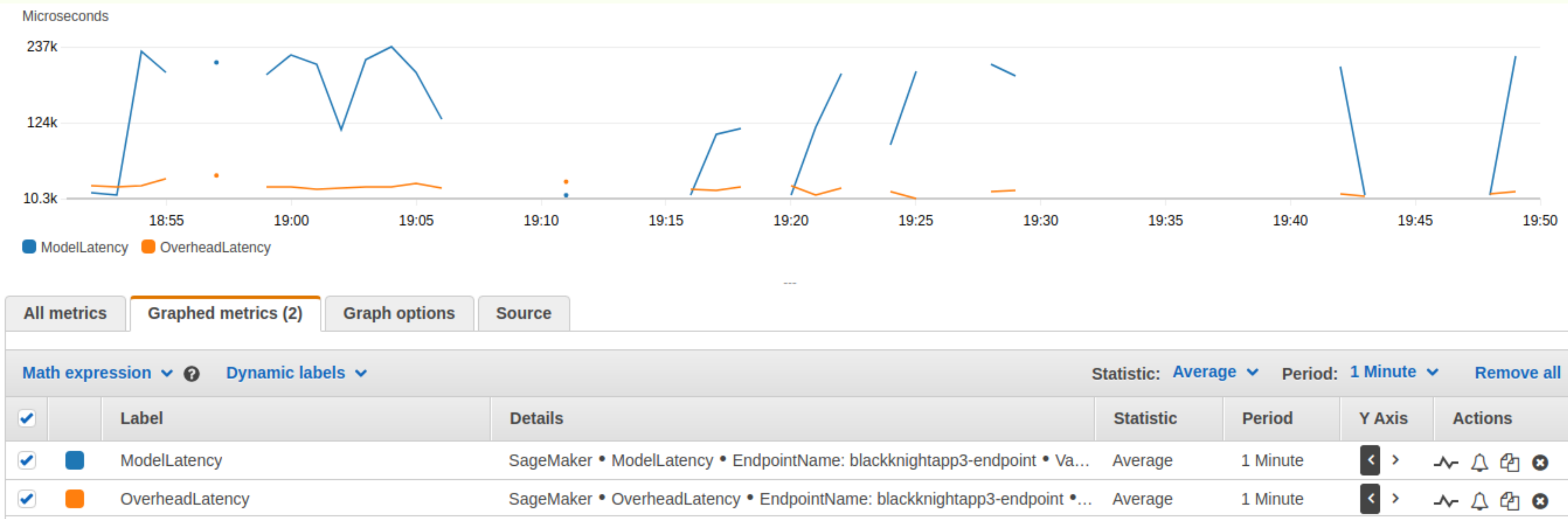

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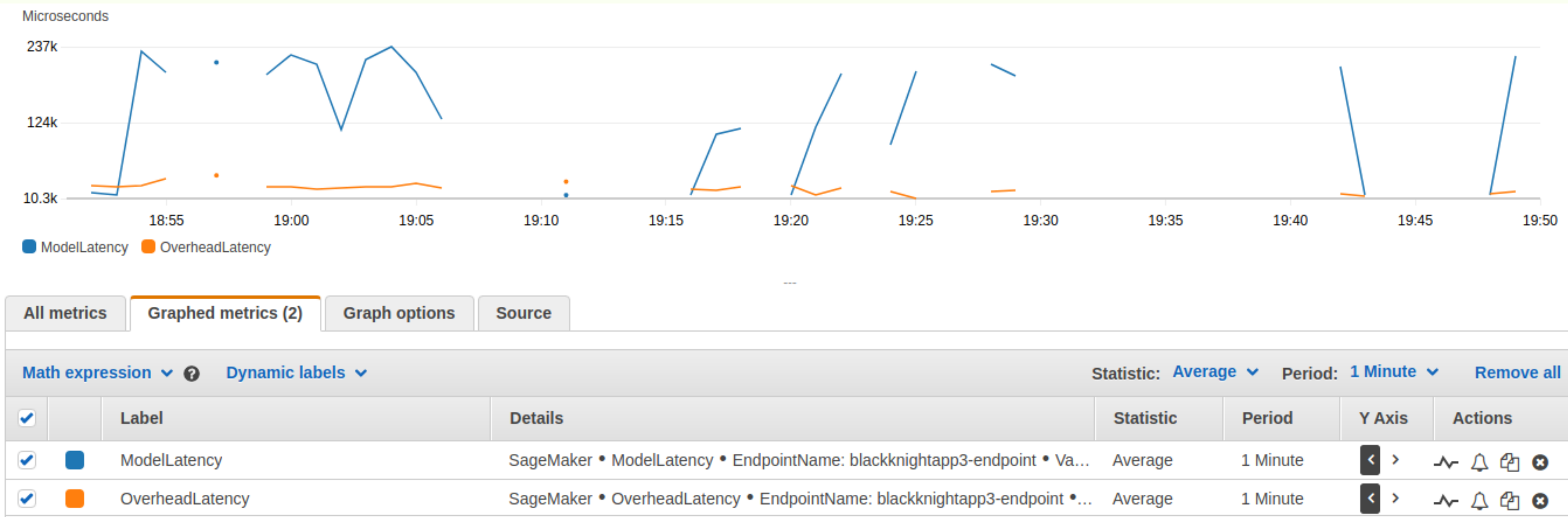

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- (the respective model sizes are 63 M and 273 M, and the shared TF-IDF vectorizer is 159 M)

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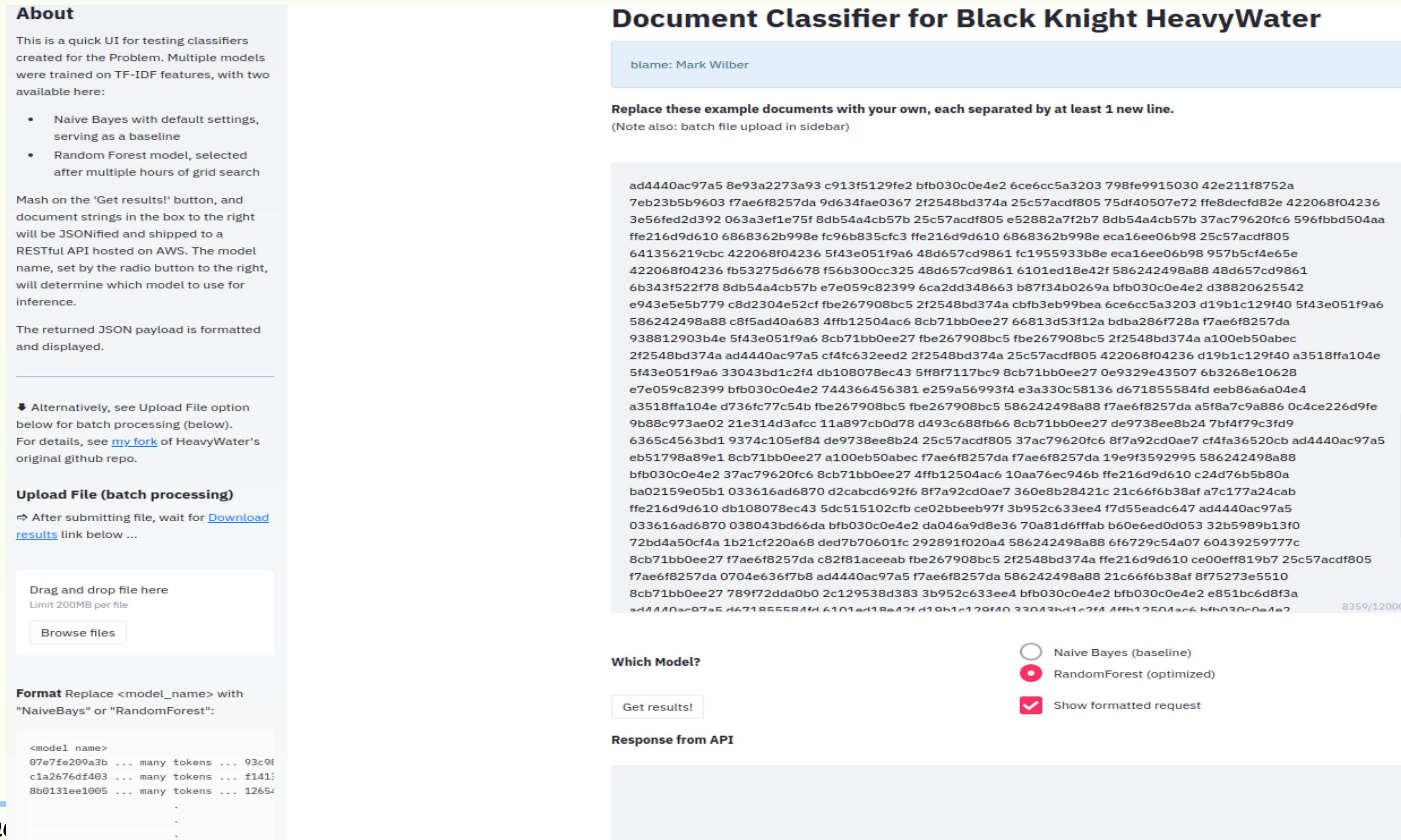

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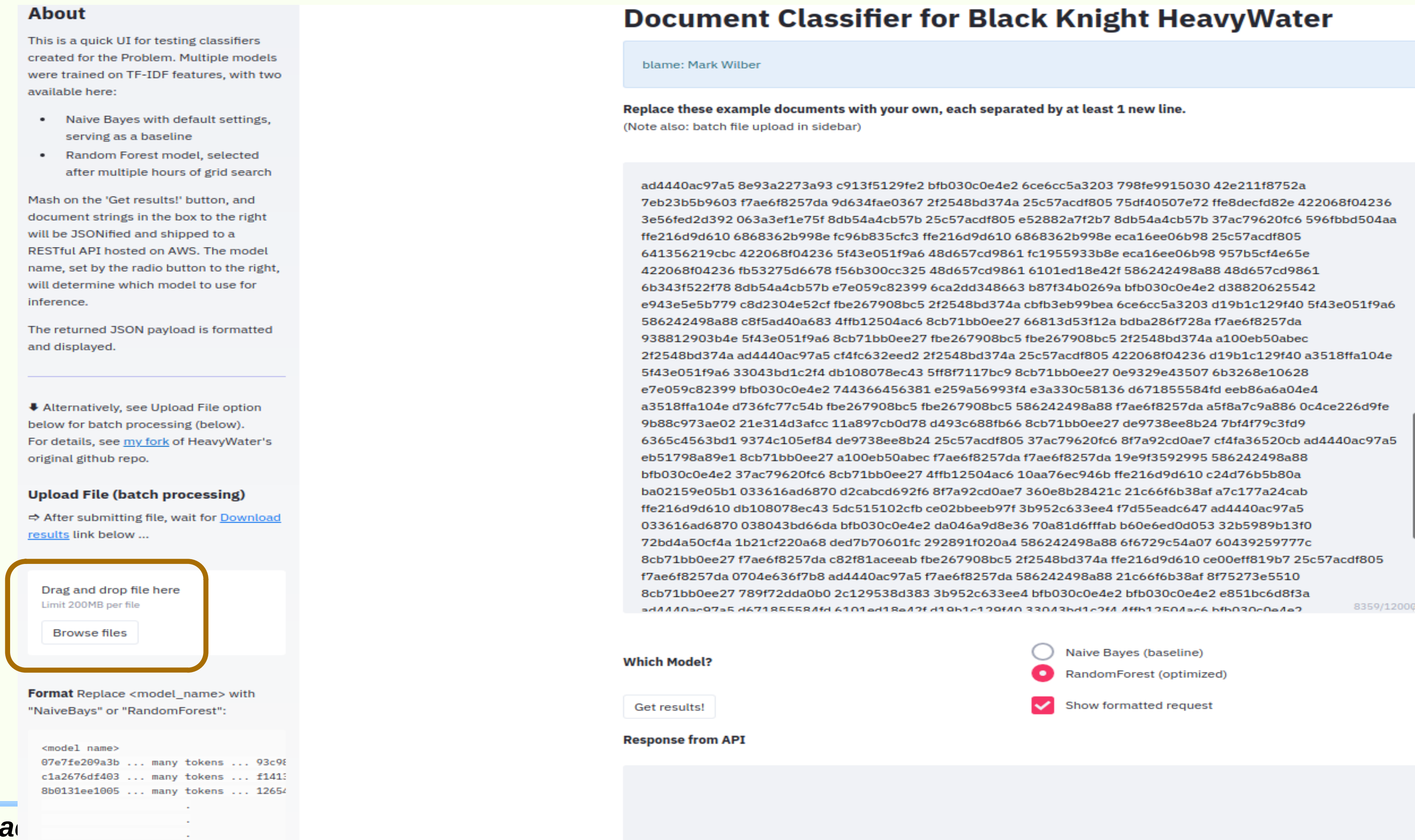

A 15-second demo

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    - sequence-based model (LSTM using sentence embeddings)

That’s all!