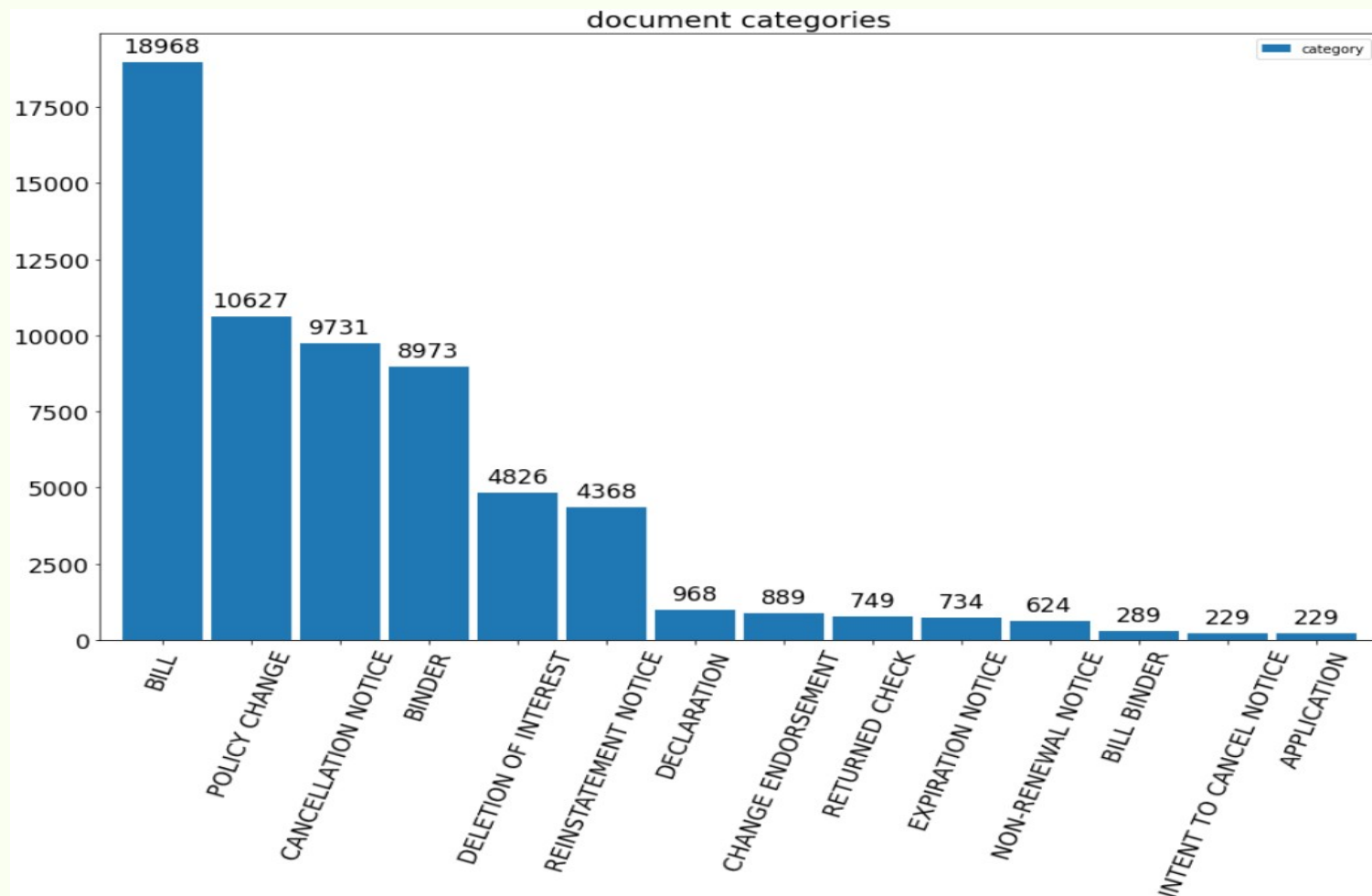


HeavyWater Machine Learning Problem

Solution by Mark Wilber

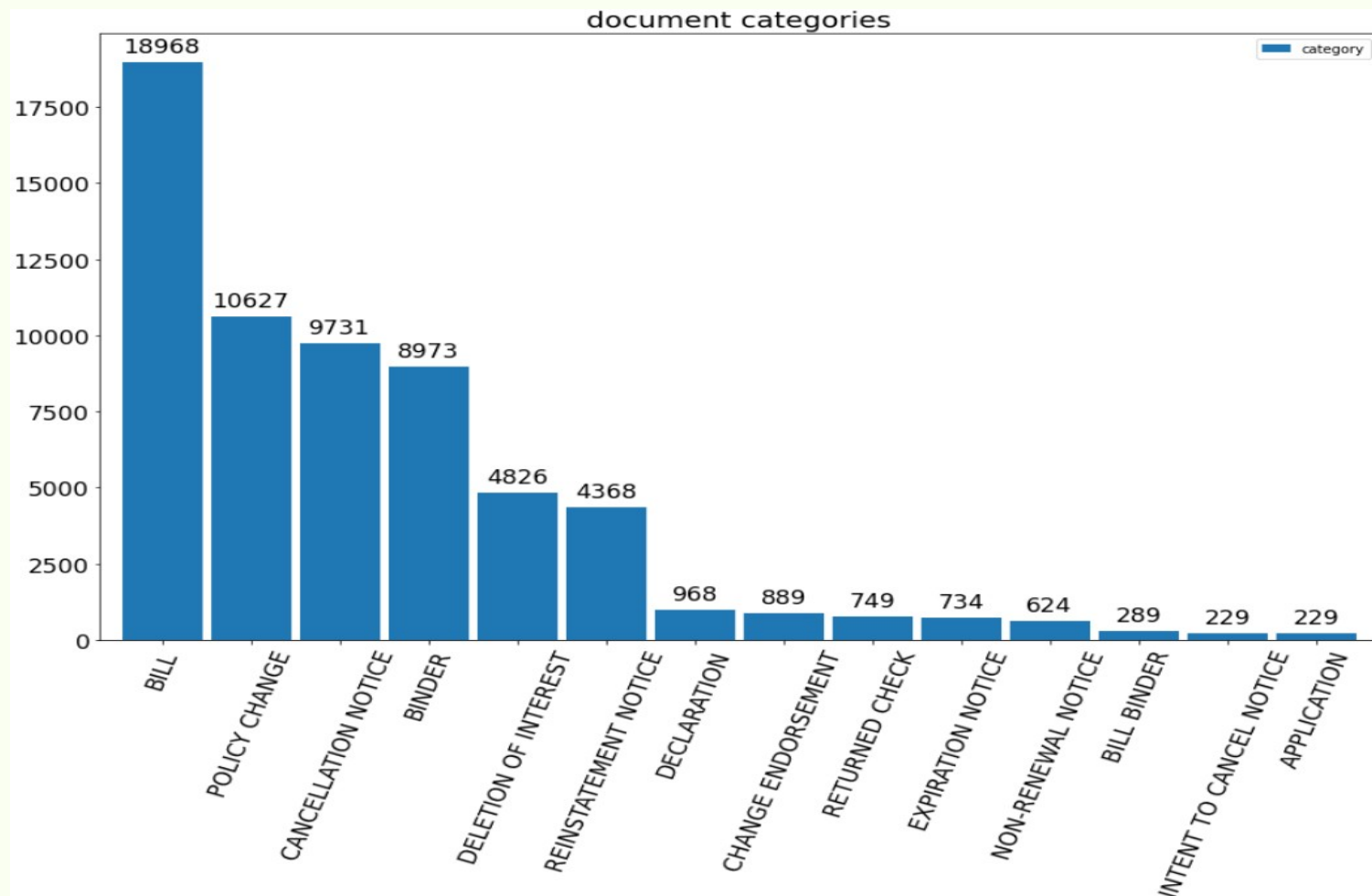
What we are dealing with

- 62 K documents, 14 categories



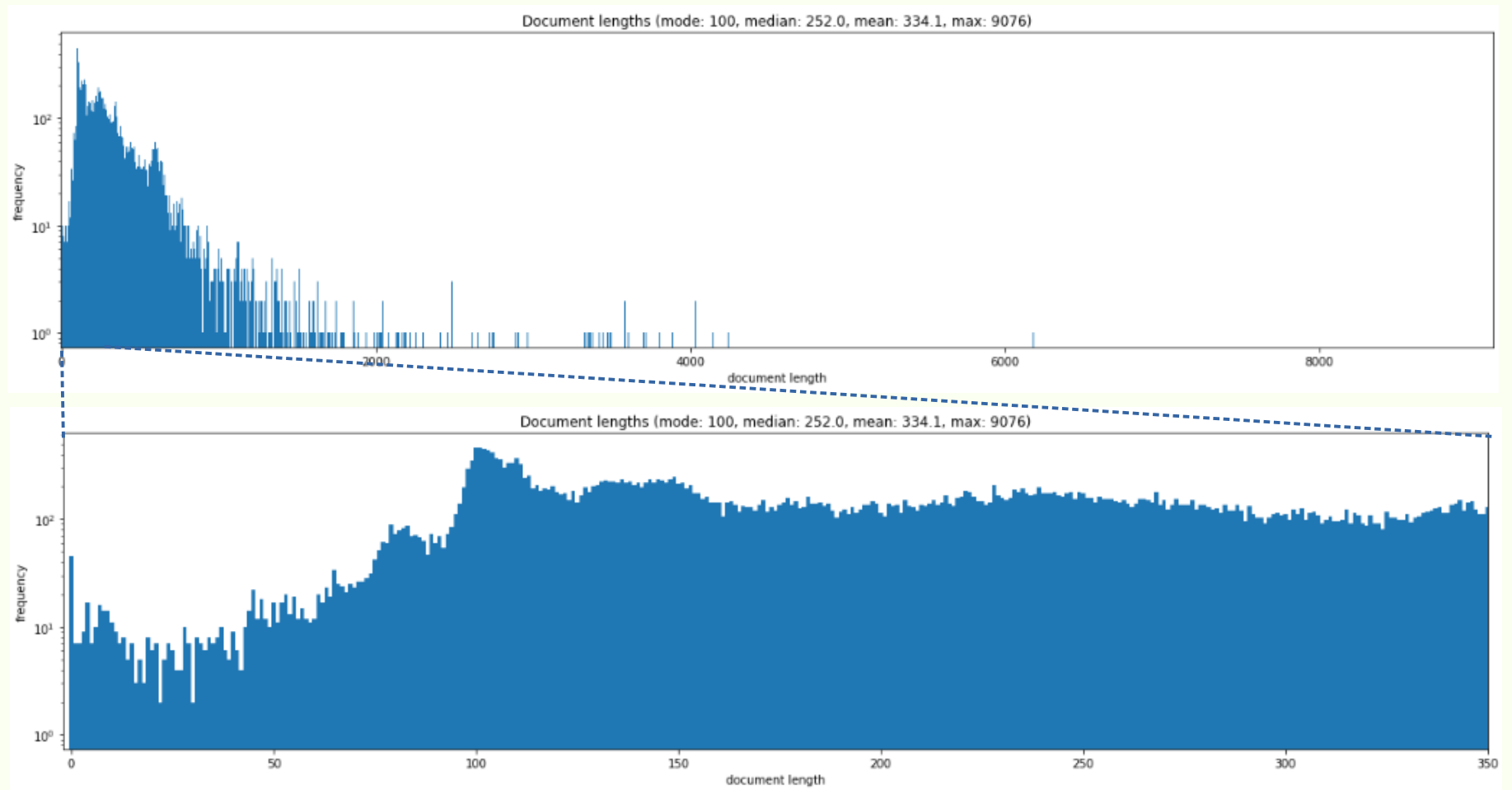
What we are dealing with

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



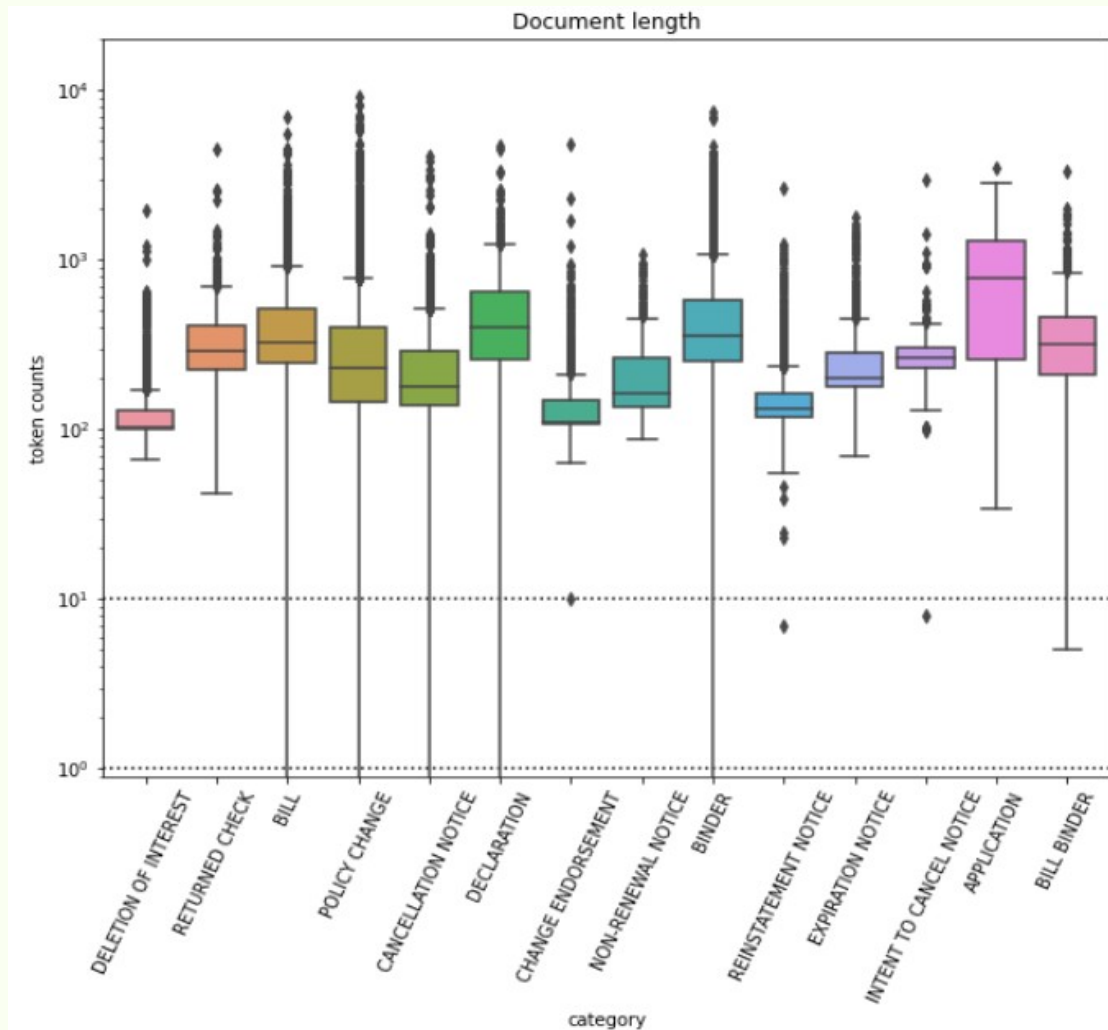
What we are dealing with

- 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](#):

Oxford Dictionary has 273,000 headwords; 171,476 of them being in current use, 47,156 being obsolete words and around 9,500 derivative words included as subentries. The dictionary contains 157,000 combinations and derivatives in bold type, and 169,000 phrases and combinations in bold italic type, making a total of over 600,000 word-forms. There is one count that puts the English vocabulary at about 1 million words — but that count presumably includes words such as Latin species names, prefixed and suffixed words, scientific terminology, jargon, foreign words of extremely limited English use and technical acronyms.

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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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4	103088	934846	0.900680
3	128487	909447	0.876209
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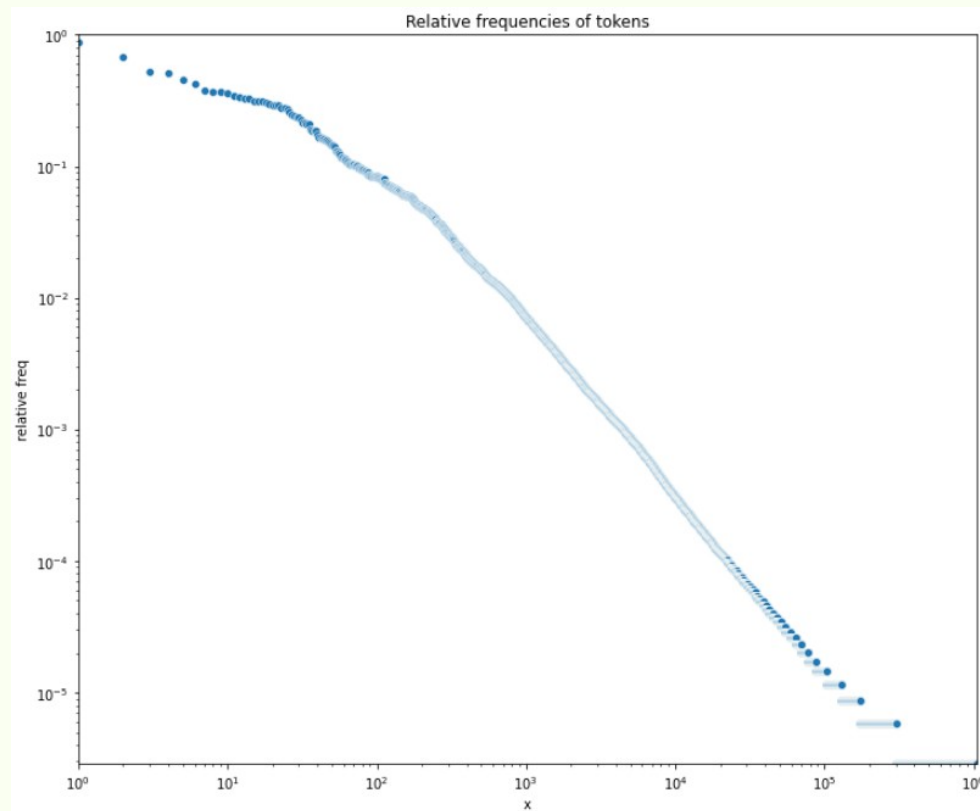
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⇒ speculation: rarely occurring terms are bogus, due to scan / OCR noise

⇒ smudges create nonsense terms

What we are dealing with

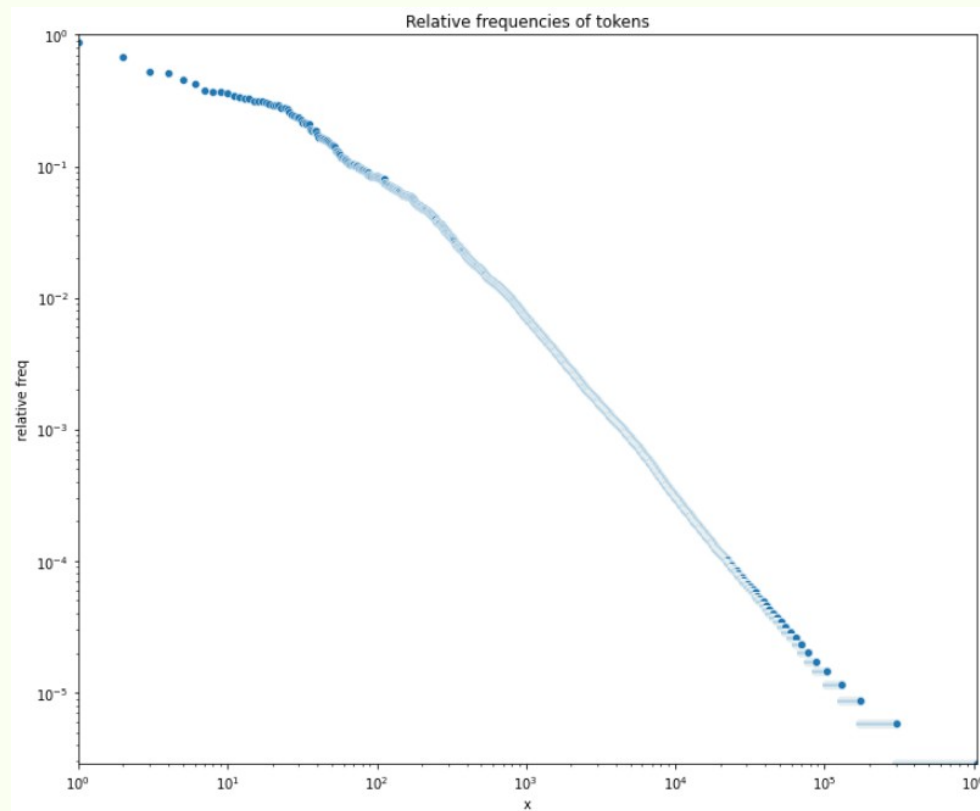
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- first ~25 tokens frequency declines weakly vs Zipf

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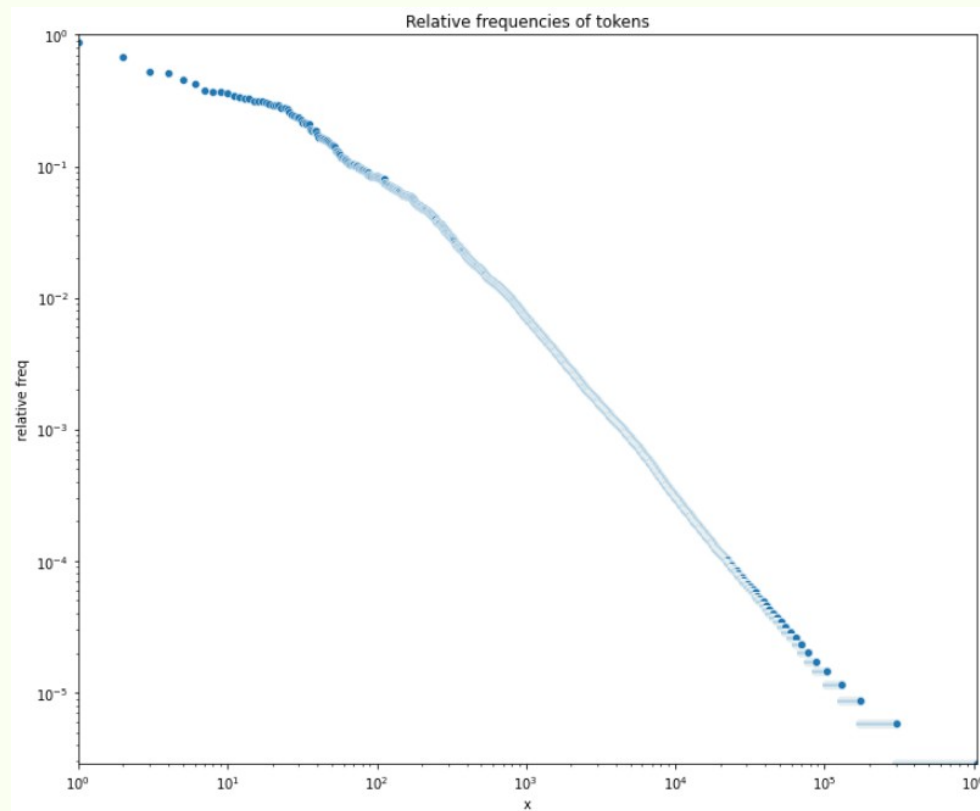
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⇒ *this corpus seems to be unusual ...*

Handling Data

Problem with stop words

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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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- stratified sampling
- 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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See [notebook/DocumentClassificationTest.ipynb](#) in [my repo](#) for details

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- default settings for baseline
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- best with `alpha=0.0139` and `norm=False` yielded substantial improvements
 - \Rightarrow model $3 \times$ larger

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- optimized model \Rightarrow 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)

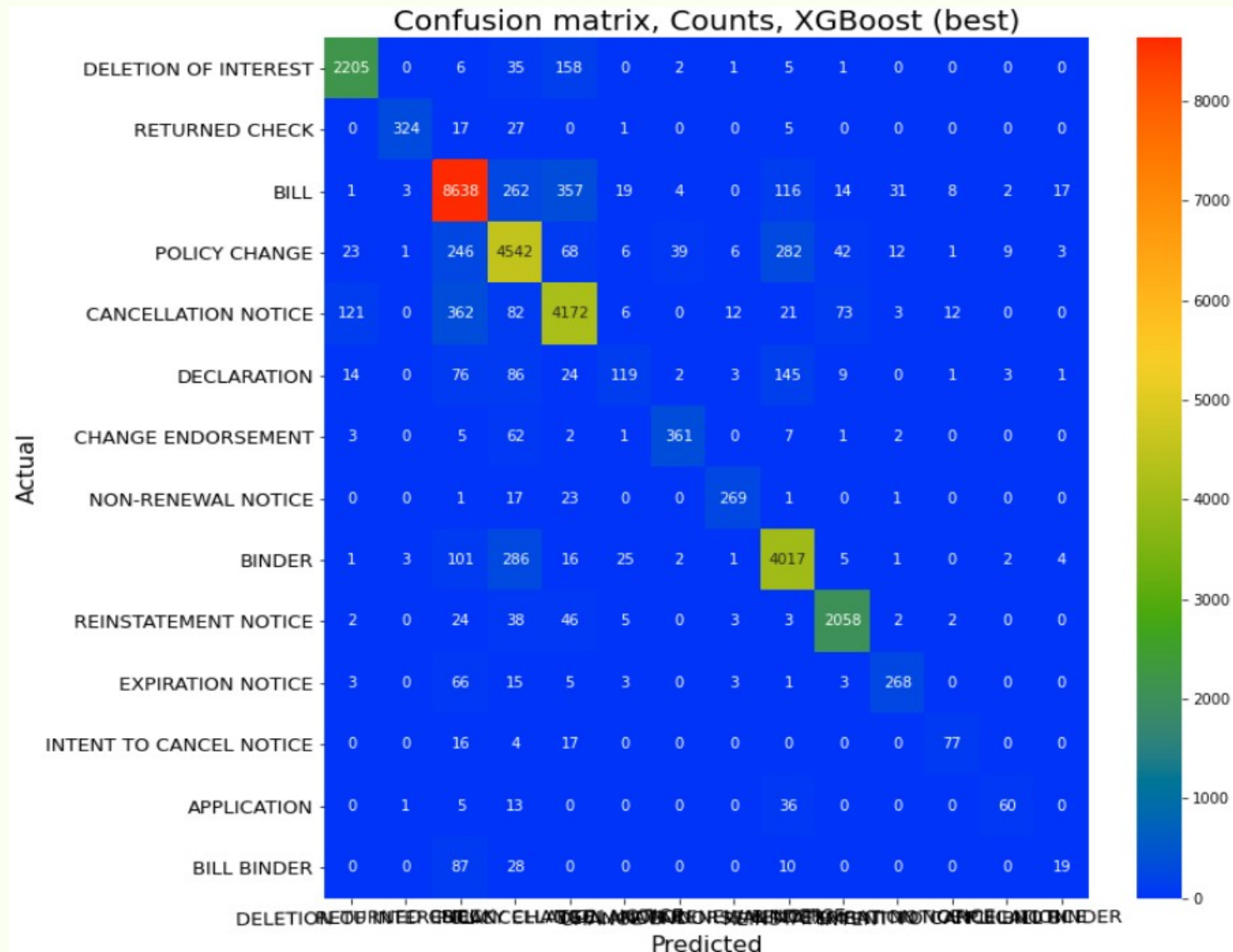
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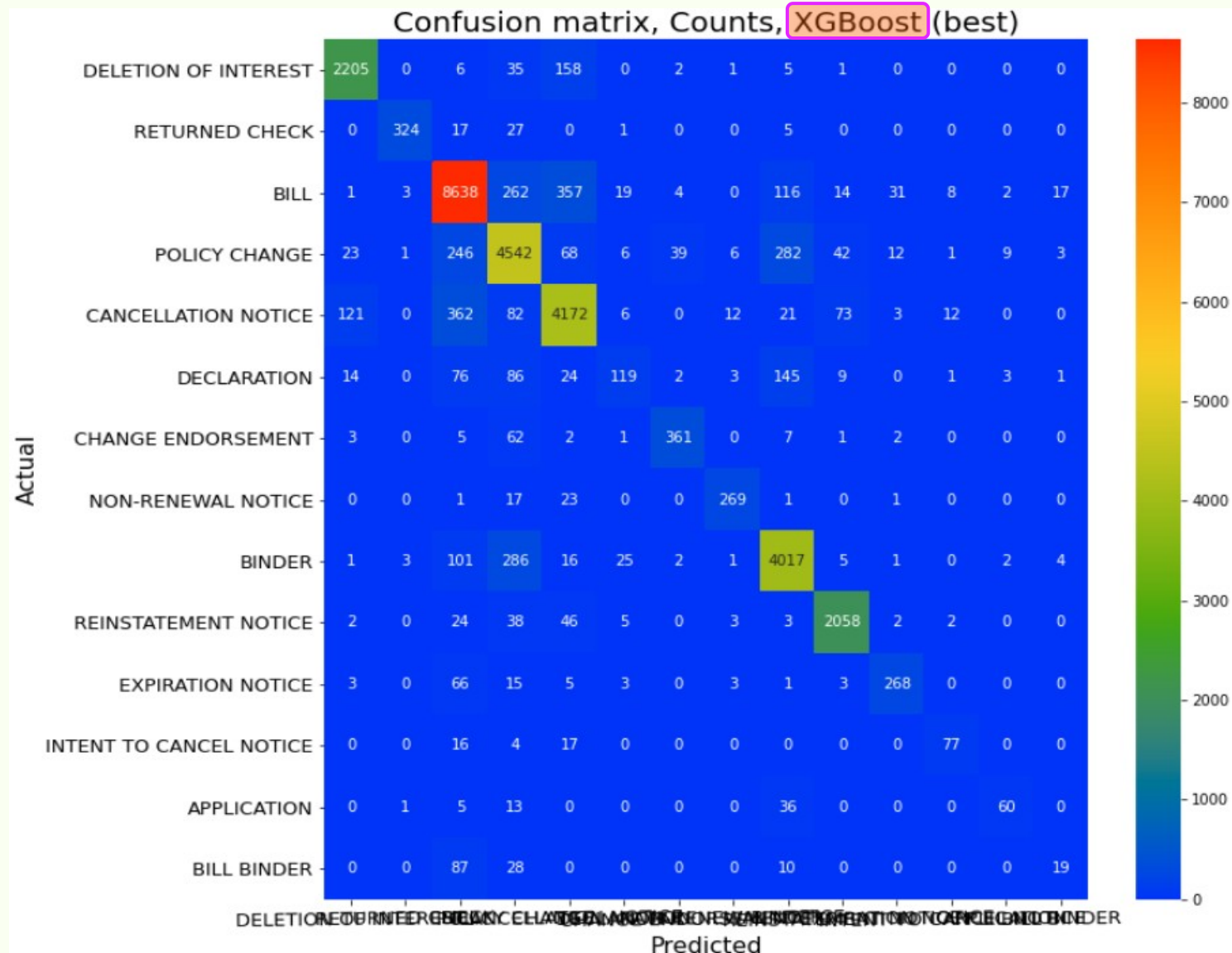
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Caution: errors in small classes 0 (10%) \Rightarrow impact macro averages most

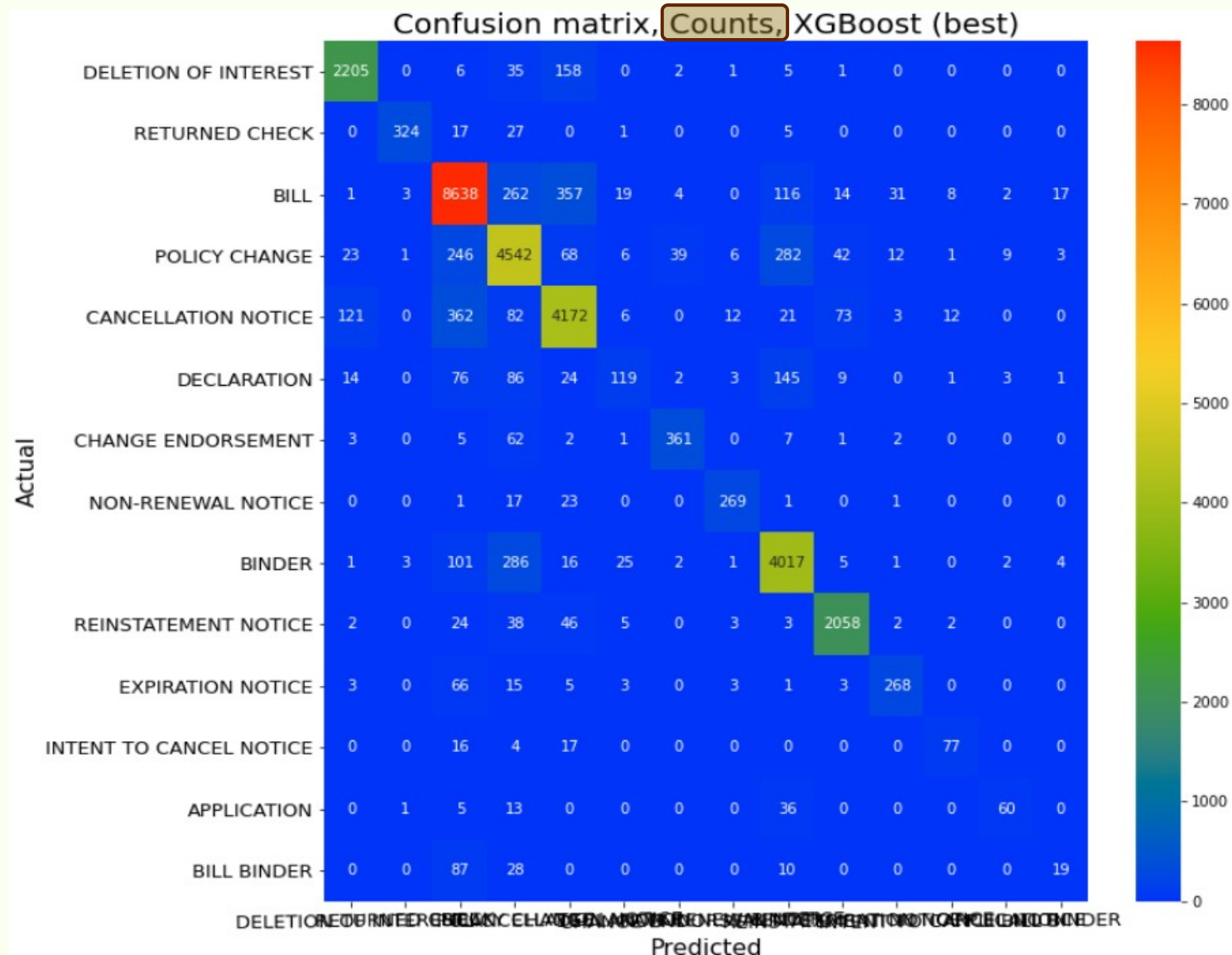
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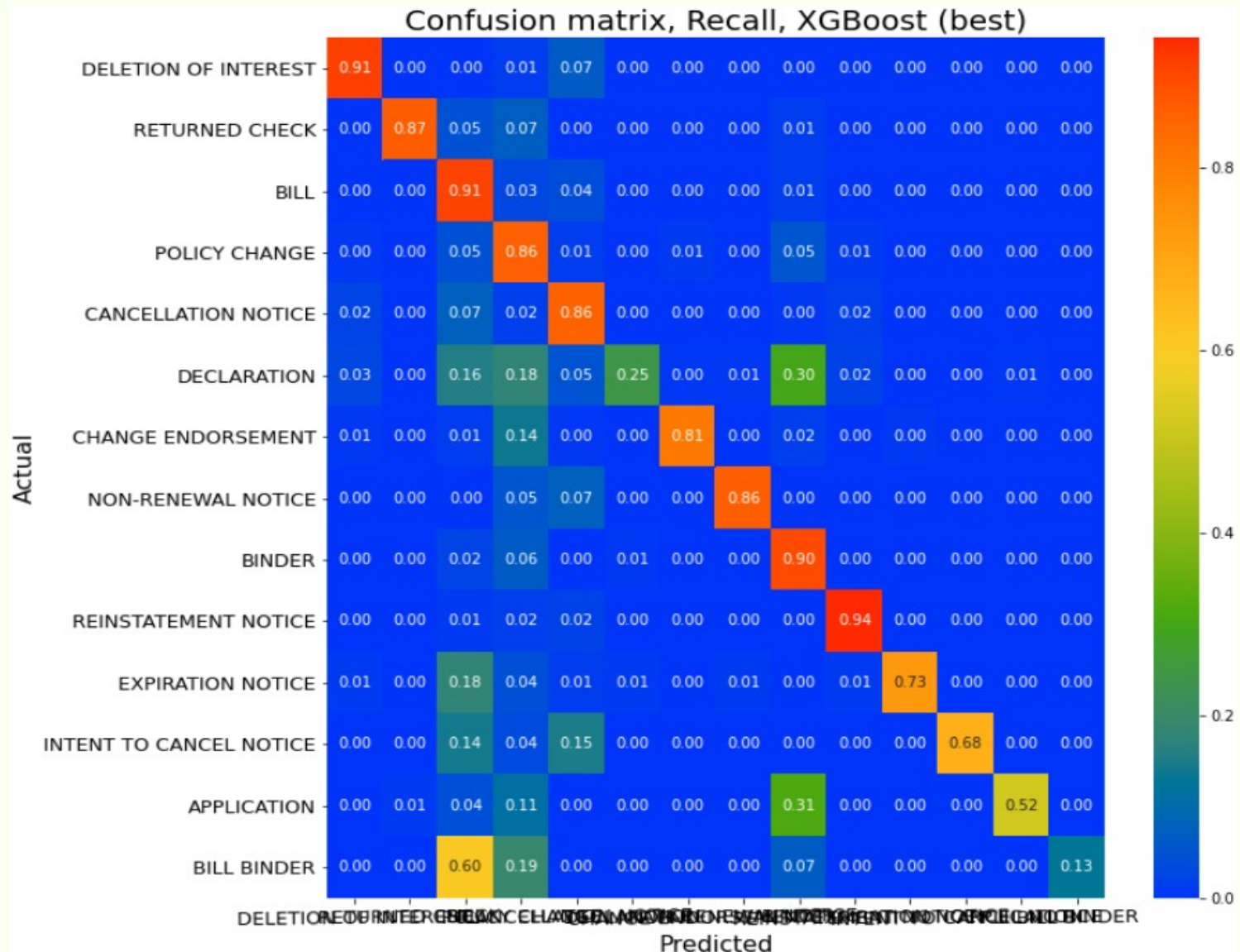
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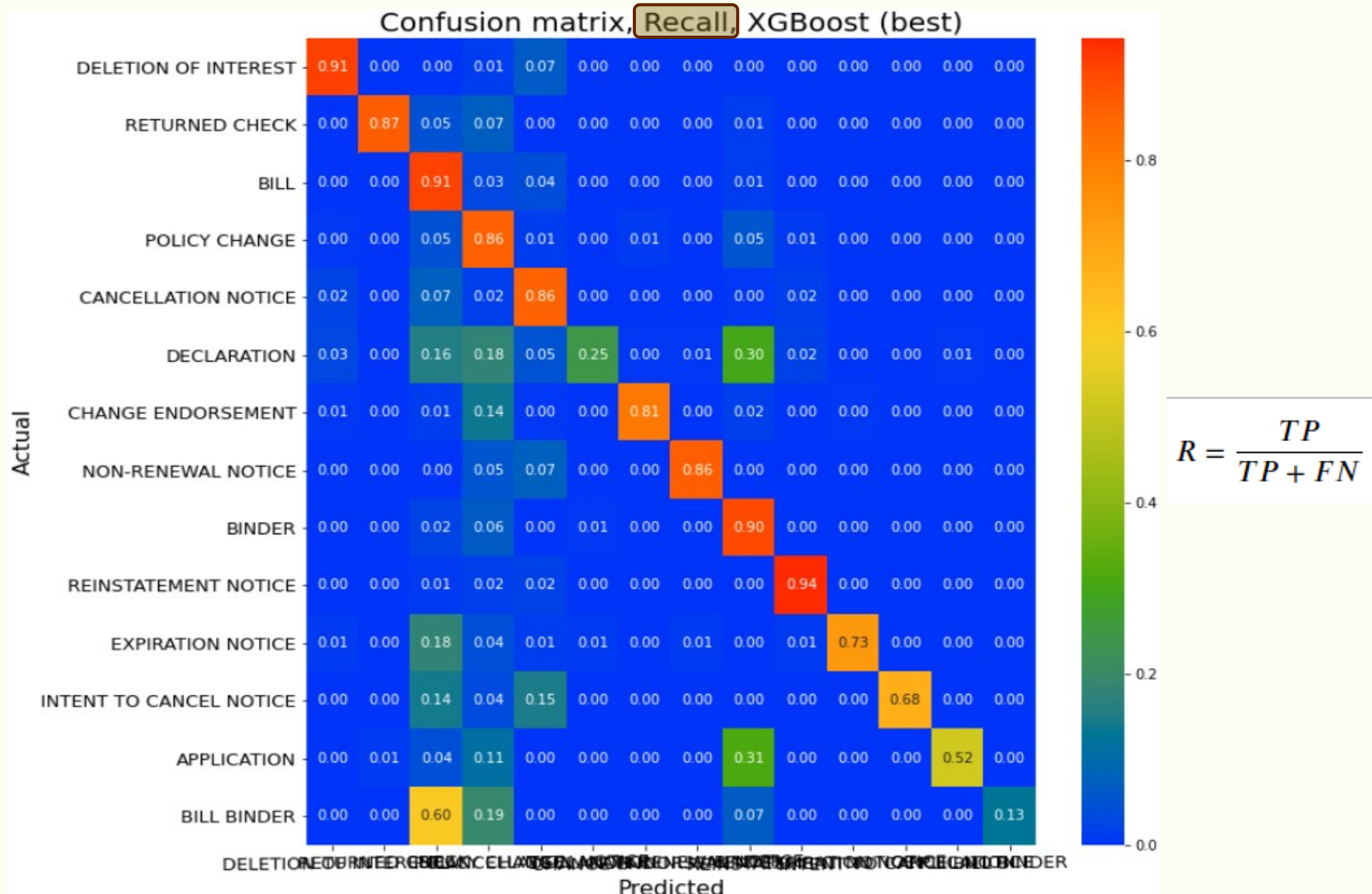
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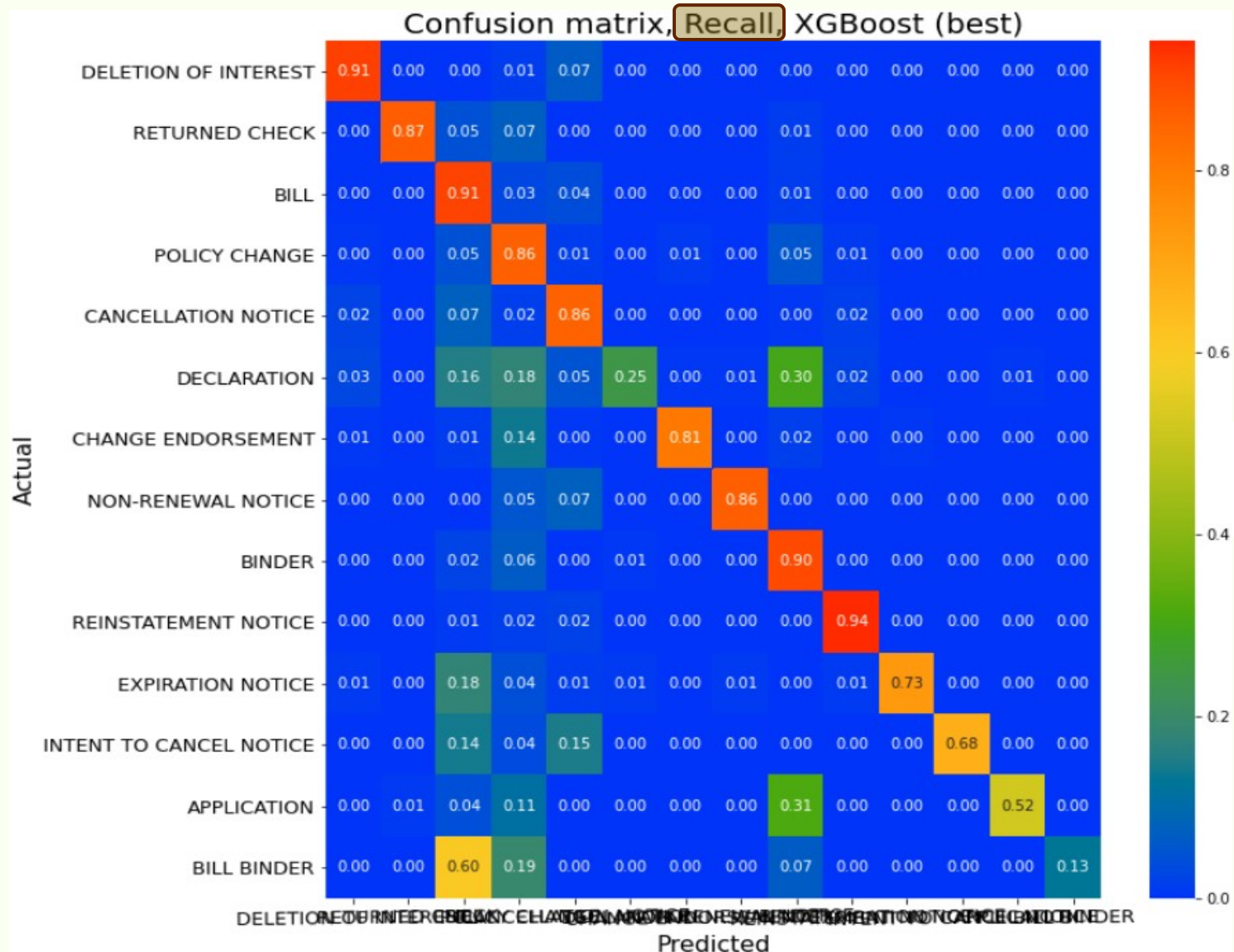
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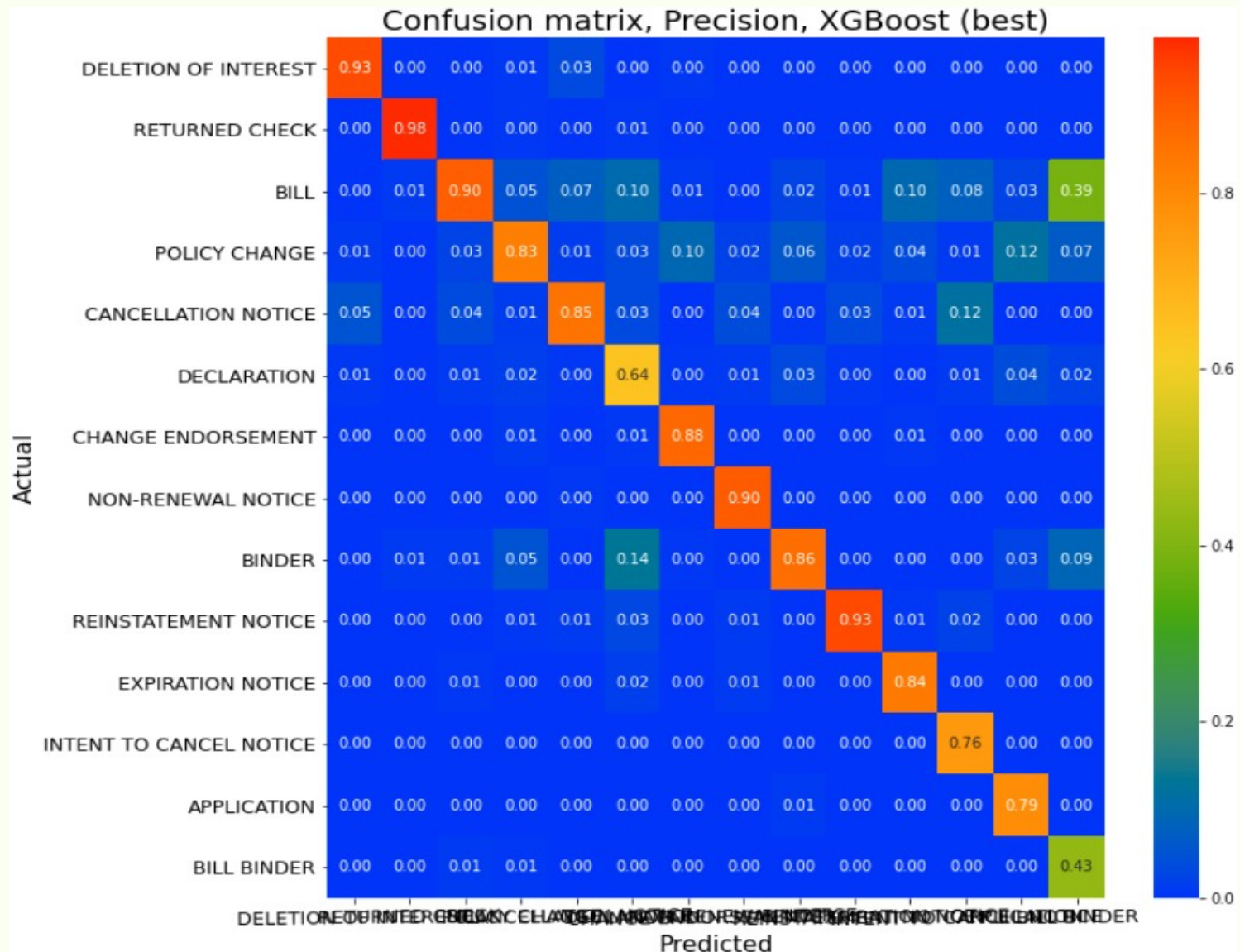


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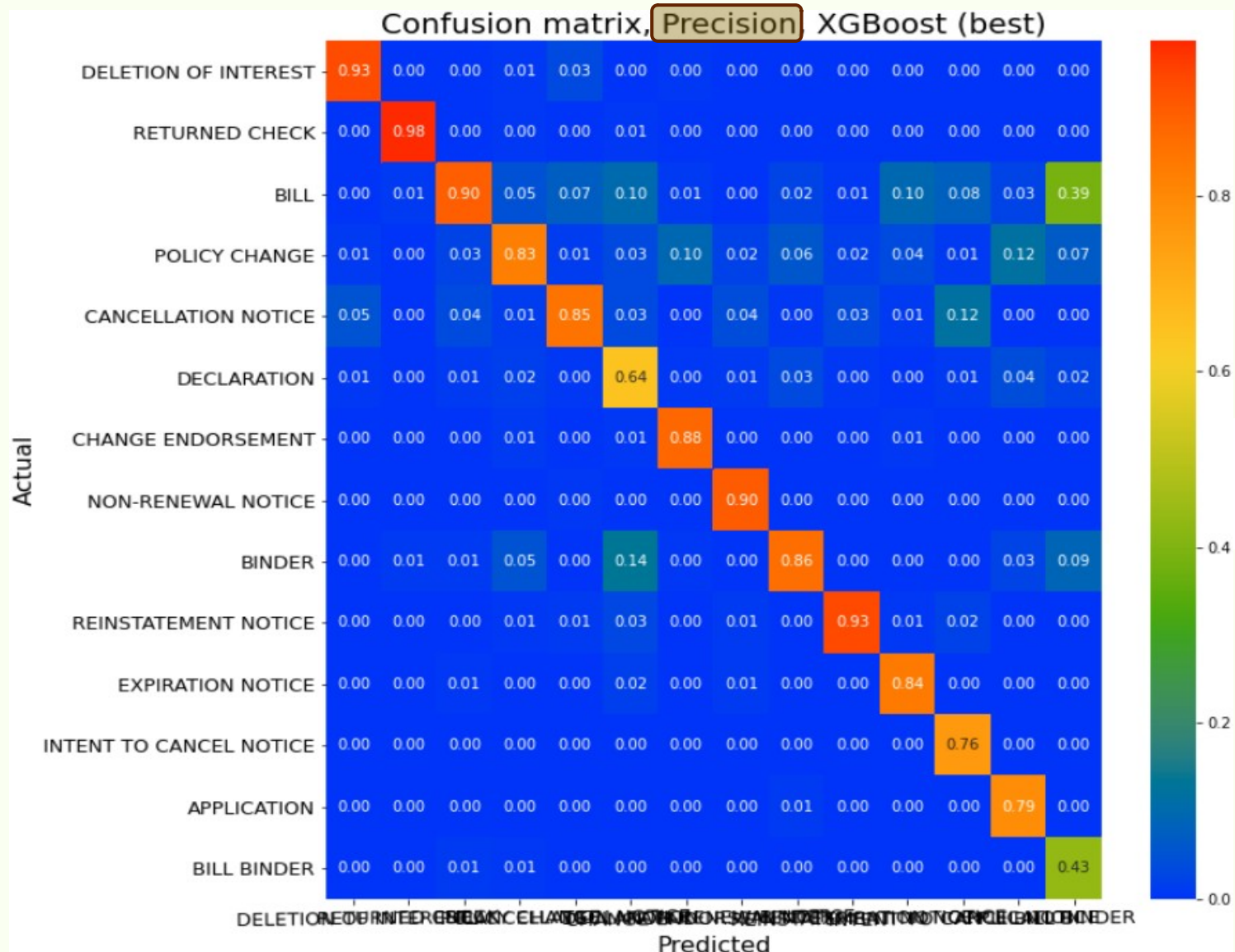


$$R = \frac{TP}{TP + FN}$$

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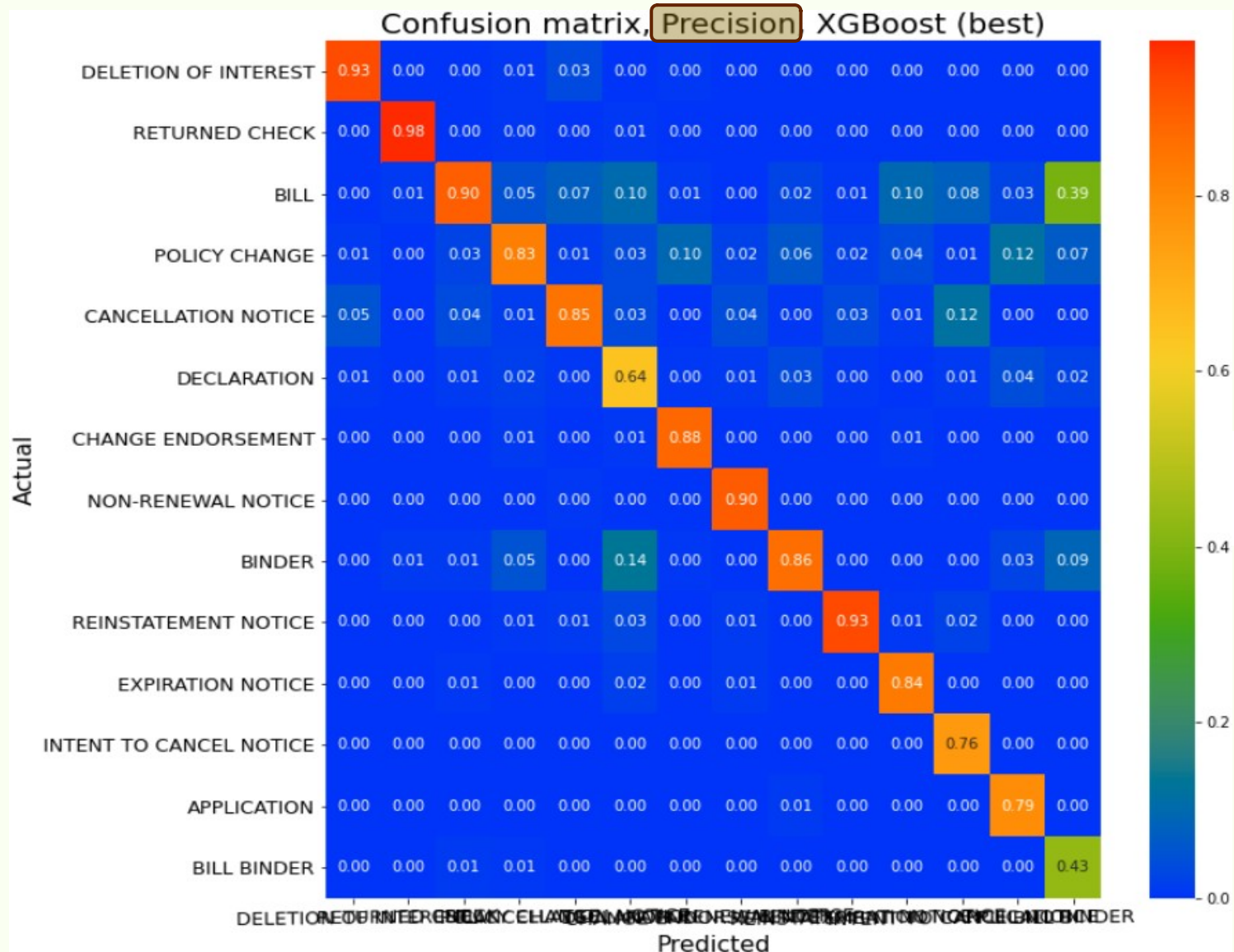


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 - ⇒ redeployed with Naive Bayes and Random Forest

Docker container

- `buildDockerImage.sh` for local testing
- `build_and_deploy.sh` for also deploying to AWS
- `Ubuntu:latest` with minimal set of versioned python packages

Deployed Solution

General notes

- Find code in [github repo](#)
- Significant learning curve, both for Docker and deployment of end points
- Learned the hard way why XGBoost training was much faster than GradientBoostingClassifier
 - XGBoost discovered GPUs on local machine when training
 - ⇒ trained model insisted on GPUS for inference
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Docker container

- `buildDockerImage.sh` for local testing
- `build_and_deploy.sh` for also deploying to AWS
- `Ubuntu:latest`, with minimal set of versioned python packages
- image size 912 MB

Deployed Endpoint

- (default) ml.m4.xlarge EC2 instance

Deployed Endpoint

- (default) ml.m4.xlarge EC2 instance
- endpoint success required extra permissions

The screenshot shows the AWS IAM console interface for a role. The 'Permissions' tab is selected, showing two applied policies: 'AWSLambdaBasicExecutionRole-e0580e60-7813-4c5b-b5de-9754d93cc1dc' (Managed policy) and 'SageMakerInvokeEndpoint' (Inline policy). The 'SageMakerInvokeEndpoint' policy is expanded, showing its JSON definition in the 'Policy summary' view.

Permissions policies (2 policies applied)

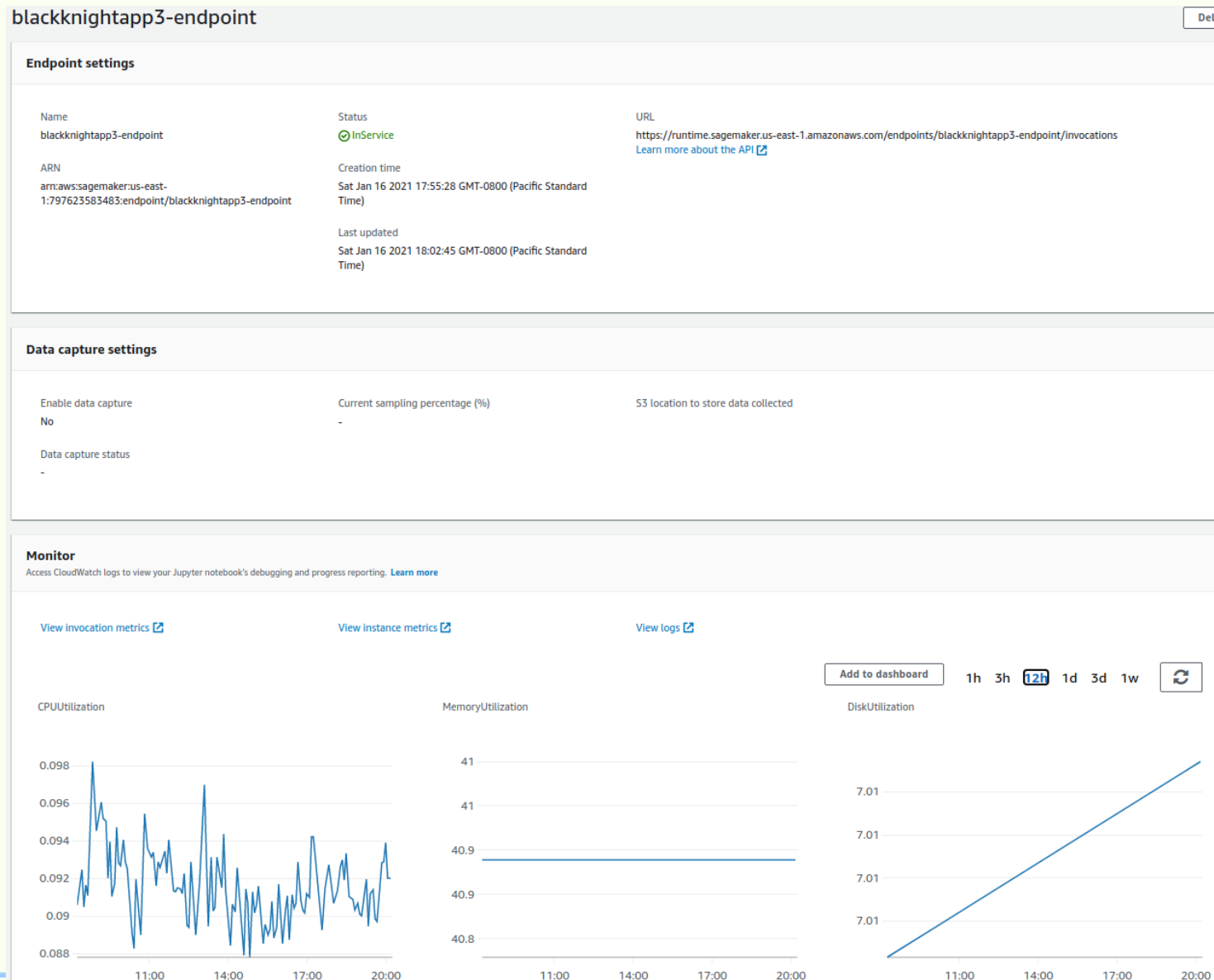
Attach policies [+ Add inline policy](#)

Policy name	Policy type
AWSLambdaBasicExecutionRole-e0580e60-7813-4c5b-b5de-9754d93cc1dc	Managed policy
SageMakerInvokeEndpoint	Inline policy

Policy summary [{} JSON](#) [Edit policy](#) [Simulate policy](#)

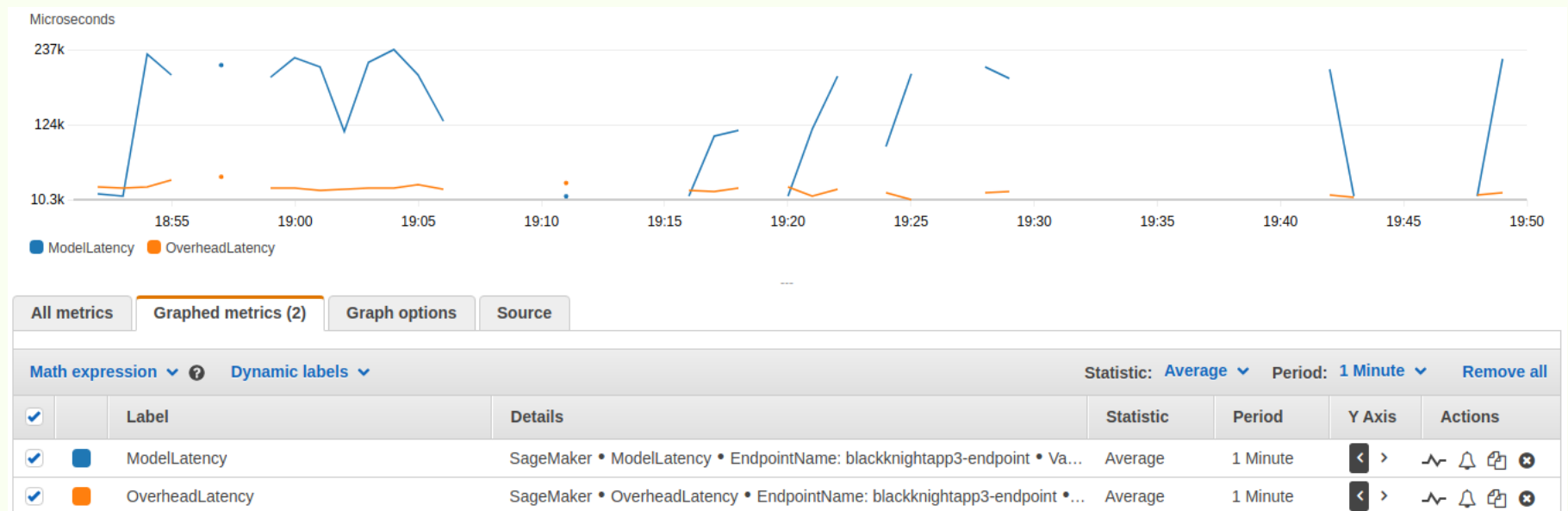
```
1 {
2   "Version": "2012-10-17",
3   "Statement": [
4     {
5       "Sid": "Stmt1464440182000",
6       "Effect": "Allow",
7       "Action": [
8         "sagemaker:InvokeEndpoint"
9       ],
10      "Resource": [
11        "*"
12      ]
13    }
14  ]
15 }
```

Deployed Endpoint



Deployed Endpoint

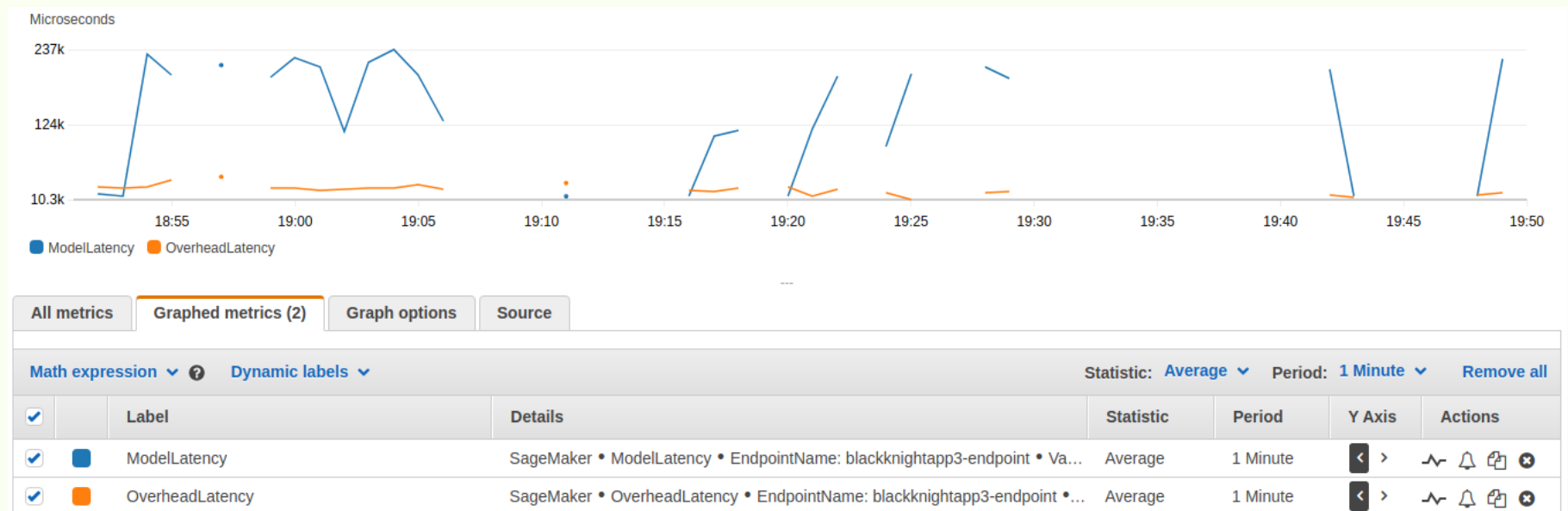
Latencies



- from isolated calls to either Naive Bayes we can see latencies of about 15 ms, while for Random Forest the latencies are about 215 ms

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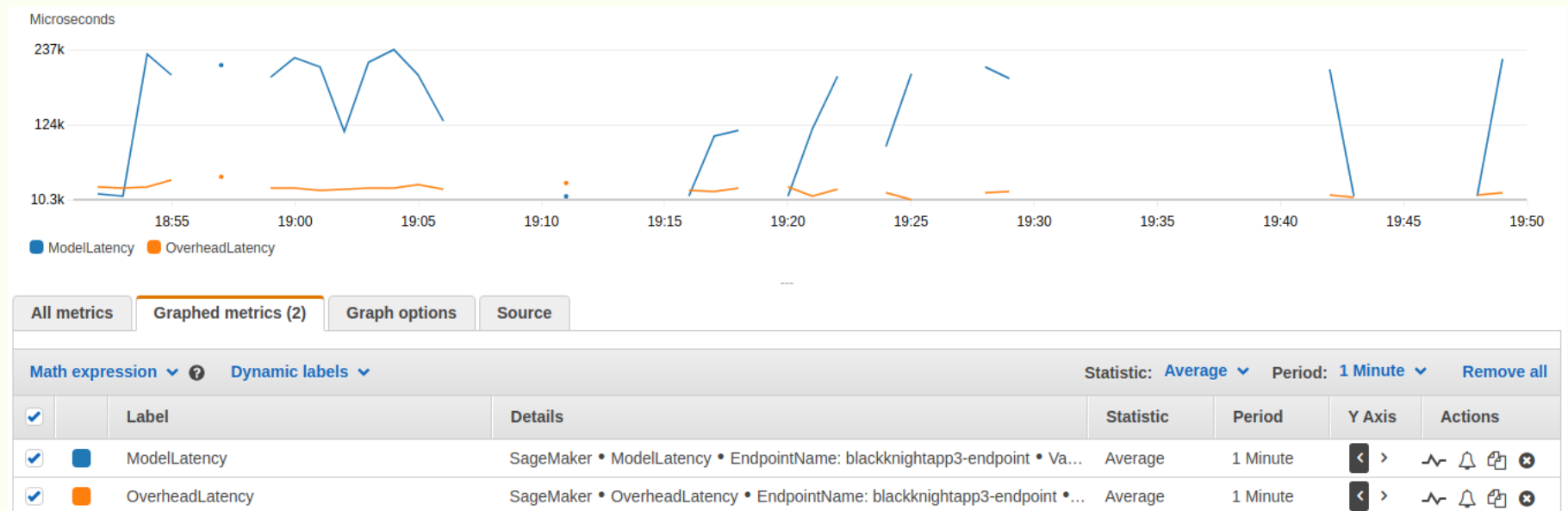
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- the Random Forest model has 250 estimators, with maximum depths of 250 – it's a little beast
- (the respective model sizes are 63 M and 273 M, and the TF-IDF vectorizer is 159 M)

Interactive UI

- Built using [streamlit](#), which is the way to go for speedy development

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About

This is a quick UI for testing classifiers created for the Problem. Multiple models were trained on TF-IDF features, with two available here:

- Naive Bayes with default settings, serving as a baseline
- Random Forest model, selected after multiple hours of grid search

Mash on the 'Get results!' button, and document strings in the box to the right will be JSONified and shipped to a RESTful API hosted on AWS. The model name, set by the radio button to the right, will determine which model to use for inference.

The returned JSON payload is formatted and displayed.

Alternatively, see Upload File option below for batch processing (below). For details, see [my fork](#) of HeavyWater's original github repo.

Upload File (batch processing)

⇒ After submitting file, wait for [Download results](#) link below ...

Drag and drop file here
Limit 200MB per file

Browse files

Format Replace <model_name> with "NaiveBays" or "RandomForest":

```
<model_name>
07e7fe209a3b ... many tokens ... 93c9f
c1a2676df403 ... many tokens ... f1411
8b0131ee1005 ... many tokens ... 12654
```

Document Classifier for Black Knight HeavyWater

blame: Mark Wilber

Replace these example documents with your own, each separated by at least 1 new line.
(Note also: batch file upload in sidebar)

```
ad4440ac977a5 8e93a2273a93 c913f5129fe2 bfb030c0e4e2 6ce6cc5a3203 798fe9915030 42e211f8752a
7eb23b5b9603 f7ae6f8257da 9d634fae0367 2f2548bd374a 25c57acdf805 75df40507e72 ffe8decfd82e 422068f04236
3e56fed2d392 063a3ef1e75f 8db54a4cb57b 25c57acdf805 e52882a7f2b7 8db54a4cb57b 37ac79620fc6 596fbbd504aa
ffe216d9d610 6868362b998e fc96b835cfc3 ffe216d9d610 6868362b998e eca16ee06b98 25c57acdf805
641356219cbc 422068f04236 5f43e051f9a6 48d657cd9861 fc1955933b8e eca16ee06b98 957b5cf4e65e
422068f04236 fb53275d6678 f56b300cc325 48d657cd9861 6101ed18e42f 586242498a88 48d657cd9861
6b343f522f78 8db54a4cb57b e7e059c82399 6ca2dd348663 b87f34b0269a bfb030c0e4e2 d38820625542
e943e5e5b779 c8d2304e52cf fbe267908bc5 2f2548bd374a cfbf3eb99bea 6ce6cc5a3203 d19b1c129f40 5f43e051f9a6
586242498a88 c8f5ad40a683 4ffb12504ac6 8cb71bb0ee27 66813d53f12a bdba286f728a f7ae6f8257da
938812903b4e 5f43e051f9a6 8cb71bb0ee27 fbe267908bc5 fbe267908bc5 2f2548bd374a a100eb50abec
2f2548bd374a ad4440ac977a5 c4f4c632eed2 2f2548bd374a 25c57acdf805 422068f04236 d19b1c129f40 a3518ffa104e
5f43e051f9a6 33043bd1c2f4 db108078ec43 5ff8f7117bc9 8cb71bb0ee27 0e9329e43507 6b3268e10628
e7e059c82399 bfb030c0e4e2 744366456381 e259a56993f4 e3a330c58136 d671855584fd eeb86a6a04e4
a3518ffa104e d736fc77c54b fbe267908bc5 fbe267908bc5 586242498a88 f7ae6f8257da a5f8a7c9a886 0c4ce226d9fe
9b88c973ae02 21e314d3afcc 11a897cb0d78 d493c688fb66 8cb71bb0ee27 de9738ee8b24 7bf4f79c3fd9
6365c4563bd1 9374c105ef84 de9738ee8b24 25c57acdf805 37ac79620fc6 8f7a92cd0ae7 cf4fa36520cb ad4440ac977a5
eb51798a89e1 8cb71bb0ee27 a100eb50abec f7ae6f8257da f7ae6f8257da 19e9f3592995 586242498a88
bfb030c0e4e2 37ac79620fc6 8cb71bb0ee27 4ffb12504ac6 10aa76ec946b ffe216d9d610 c24d76b5b80a
ba02159e05b1 033616ad6870 d2cabcd692f6 8f7a92cd0ae7 360e8b28421c 21c66f6b38af a7c177a24cab
ffe216d9d610 db108078ec43 5dc515102c7b ce02bbbeb97f 3b952c633ee4 f7d55eadc647 ad4440ac977a5
033616ad6870 038043bd66da bfb030c0e4e2 da046a9d8e36 70a81d6ffab b60e6ed0d053 32b5989b13f0
72bd4a50cf4a 1b21cf220a68 ded7b70601fc 292891f020a4 586242498a88 6f6729c54a07 60439259777c
8cb71bb0ee27 f7ae6f8257da c82f81aceab fbe267908bc5 2f2548bd374a ffe216d9d610 ce00eff819b7 25c57acdf805
f7ae6f8257da 0704e636f7b8 ad4440ac977a5 f7ae6f8257da 586242498a88 21c66f6b38af 8f75273e5510
8cb71bb0ee27 789f72dda0b0 2c129538d383 3b952c633ee4 bfb030c0e4e2 bfb030c0e4e2 e851bc6d8f3a
ad4440ac977a5 d671855584fd 6101ed18e42f d19b1c129f40 33043bd1c2f4 4ffb12504ac6 bfb030c0e4e2
```

8359/12000

Which Model?

Get results!

Response from API

- ☐ Naive Bayes (baseline)
☒ RandomForest (optimized)
☒ Show formatted request

A 15-second demo

Next steps?

- LSTM
 - [I've done this](#) with a different text classification problem ([notebook](#))

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 - sequence-based model (LSTM using sentence embeddings)

That's all!