The speech we miss: How keyword-based data collection obscures youth participation in online political discourse

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Digisurvor workshop
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Detecting and correcting bias in linked data sources

The speech we miss: How Keyword-Based Data Collection Obscures Youth Participation in Online Political Discourse

Adina Gitomer, Sarah Shugars, Ryan J. Gallagher, Stefan McCabe, Brooke Foucault Welles

Computational Communication Research, 5(1). 2023.




RIP Twitter API 🪦

```
url = 'https://api.twitter.com

response = requests.request(
    "GET", url,
    params= {
    query = 'Trump OR election OR fascism'
    })
```

List of "political" keywords

Capturing "Political" Speech

Keyword search implicitly assumes
political content looks like:

Trump lost the election!

Capturing “Political” Speech

Keyword search implicitly assumes political content looks like:

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What political speech actually looks like

Capturing "Political" Speech

Keyword classifier

Trump lost the **election**!

Yes, election-related

Not election-related

The Speech We Miss

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RQ1:
How big of a problem is this?

The Speech We Miss

Trump lost the election!

Keyword classifier

Yes, election-related

Not election-related

RQ1:
How big of a problem is this?

RQ2:
Is there variation by **age**?

Data Matching

Hughes et al. (2020)
Shugars et al. (2021)

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- Panel of 1.6 million Twitter users matched to US voting records

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Match if I'm the **only** "Sarah Shugars" registered to vote in "New Brunswick, NJ"

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- Demographically representative of Twitter users overall
  - Youngest users were 17 in 2017

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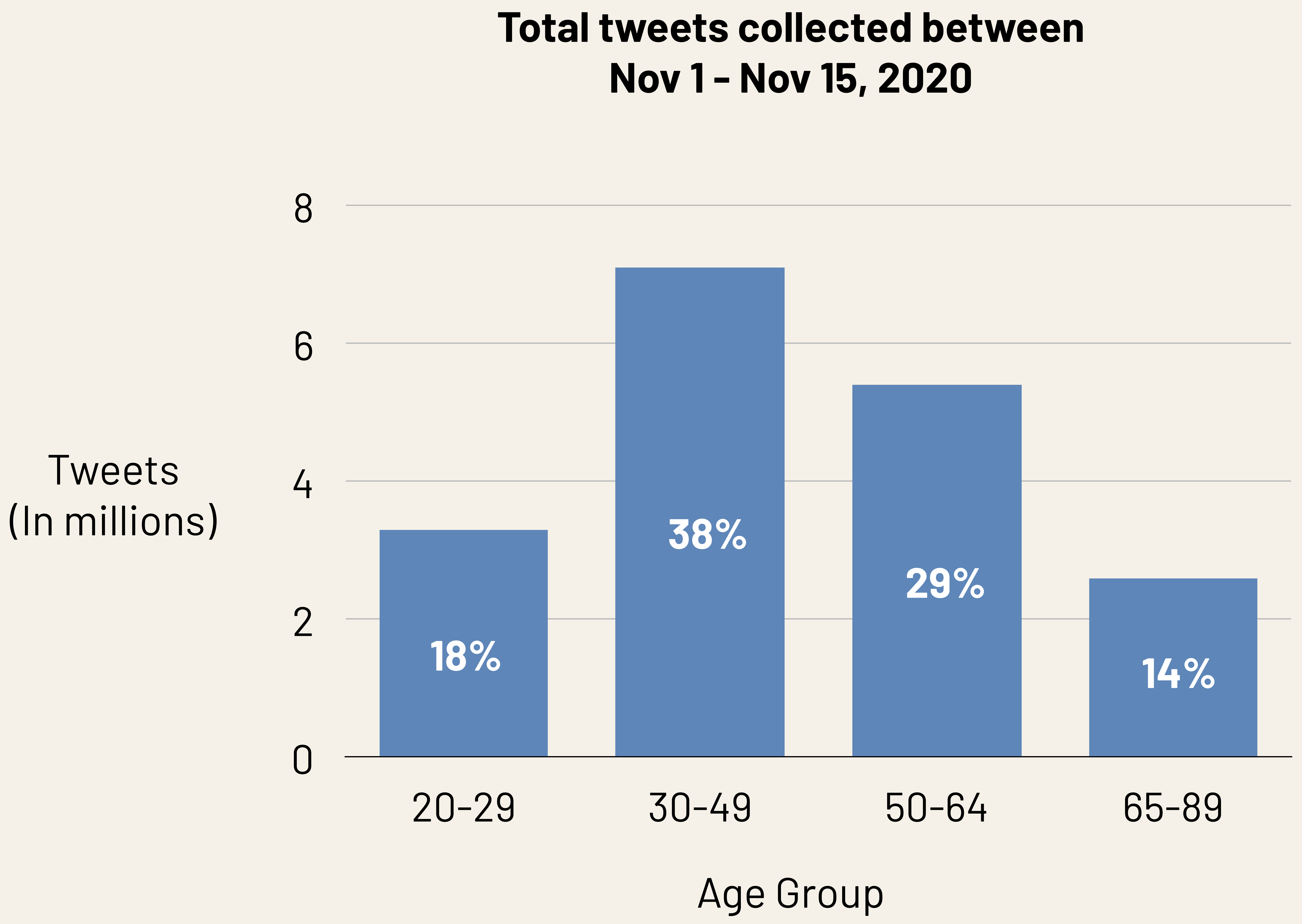
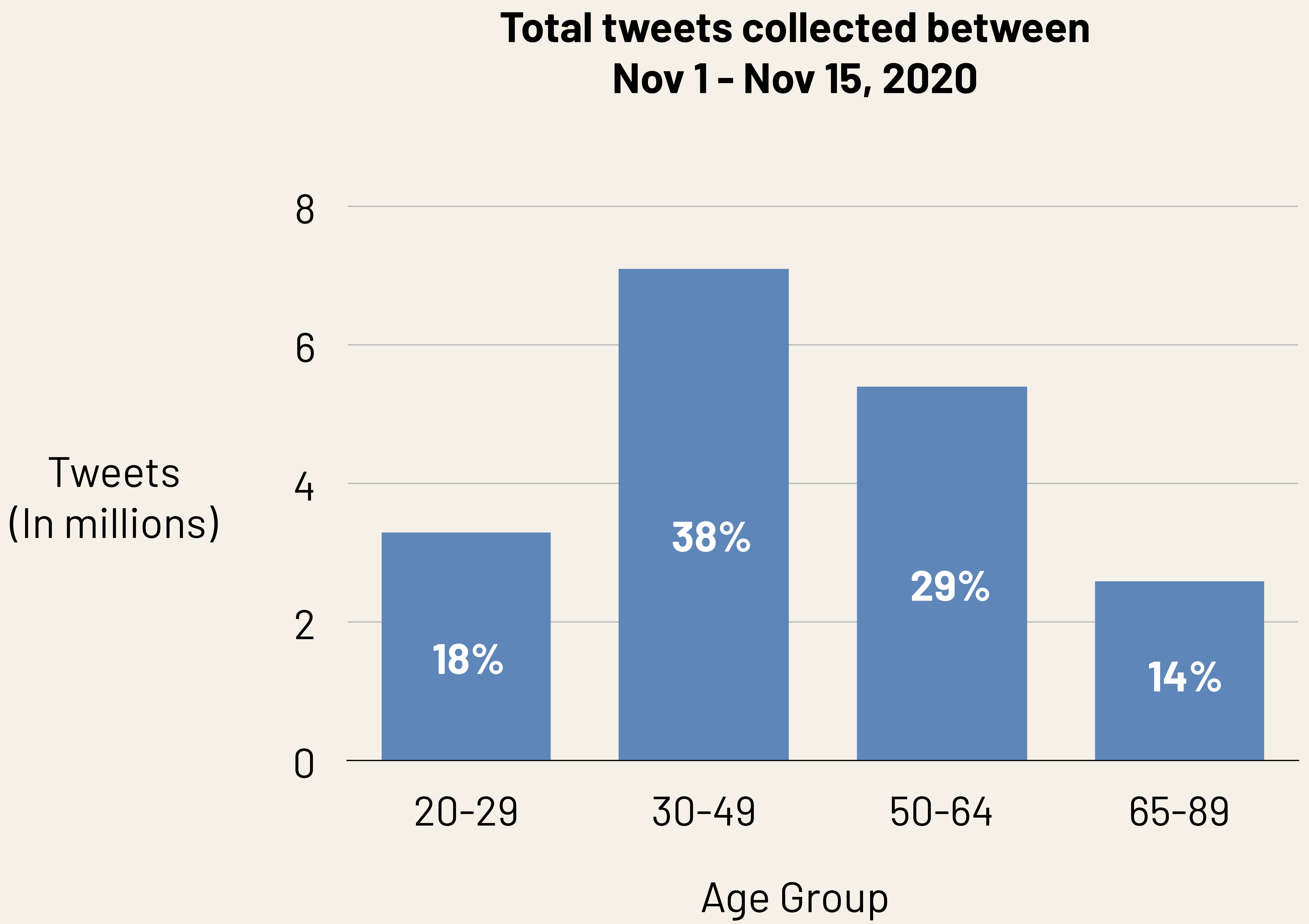
Data



Total tweets collected between
Nov 1 - Nov 15, 2020
8
6
4
2
0
Tweets
(In millions)
18%
38%
29%
14%
20-29
30-49
50-64
65-89
Age Group

Data

We collect <u>all</u> posts made by panelists between Nov 1 - Nov 15 2020



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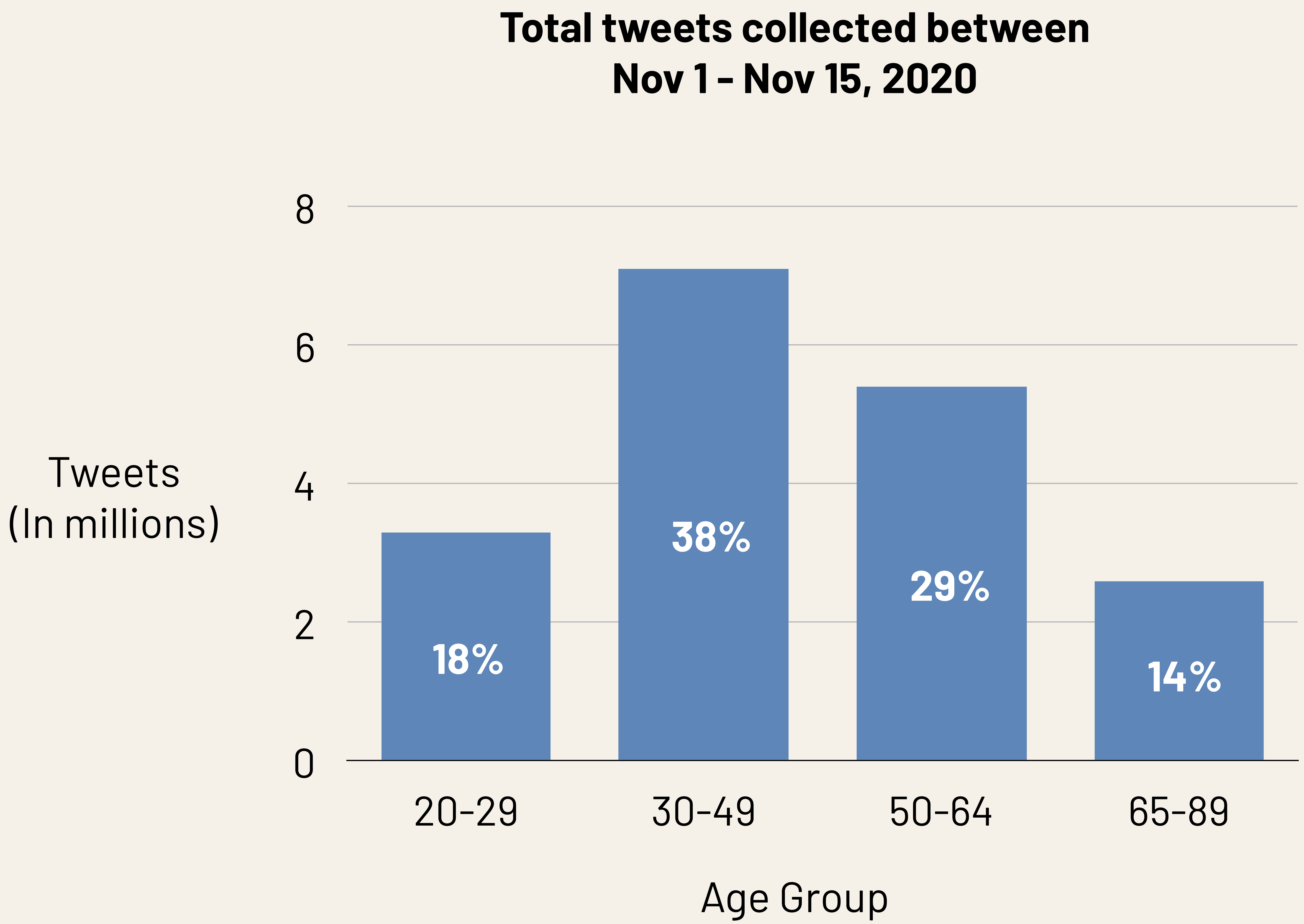
- ➡ Which tweets would be retrieved using keyword-based search?



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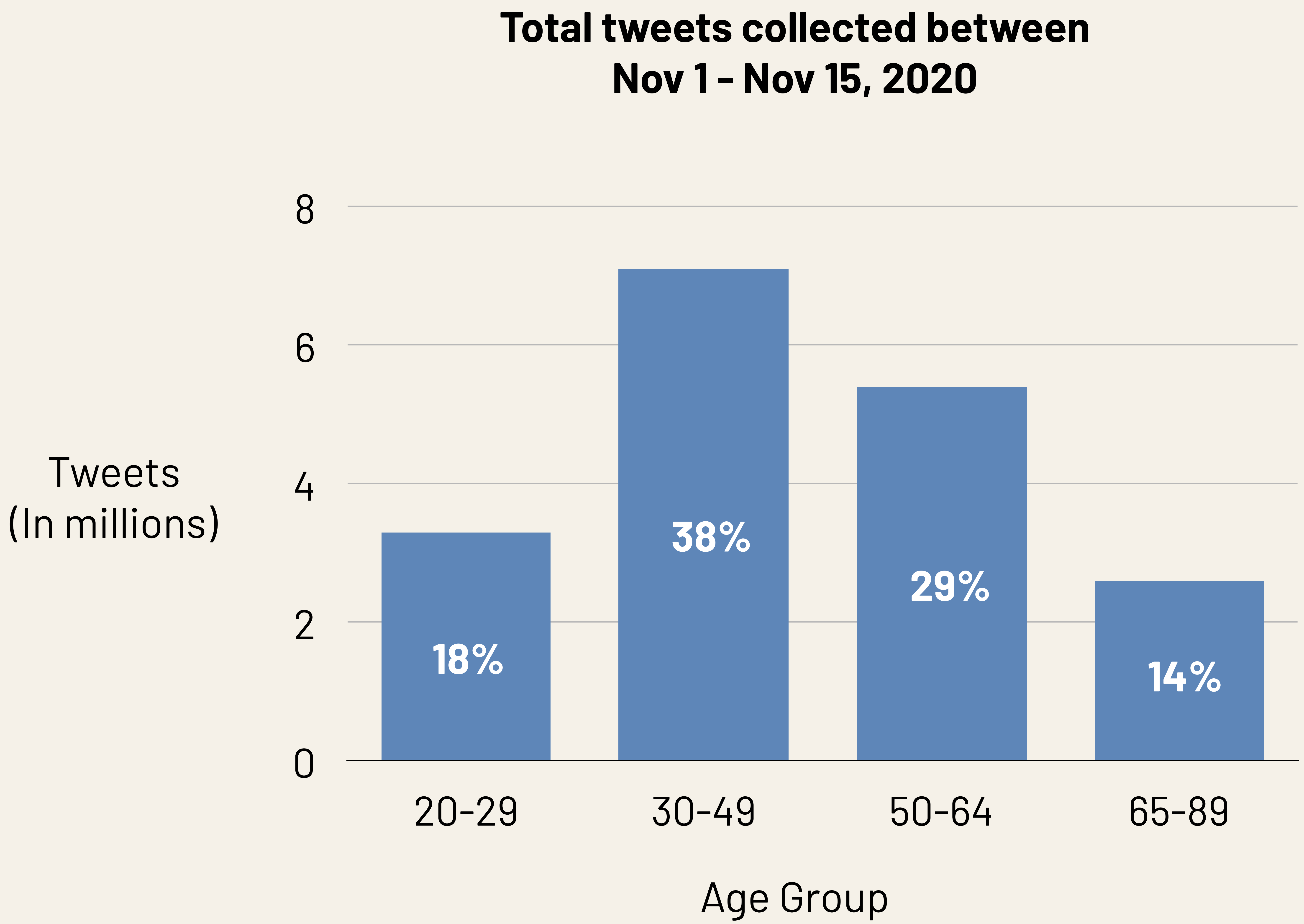
- ➡ Which tweets are actually election-related? (Via handcoding)



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- ➡ Which tweets would be retrieved using keyword-based search?
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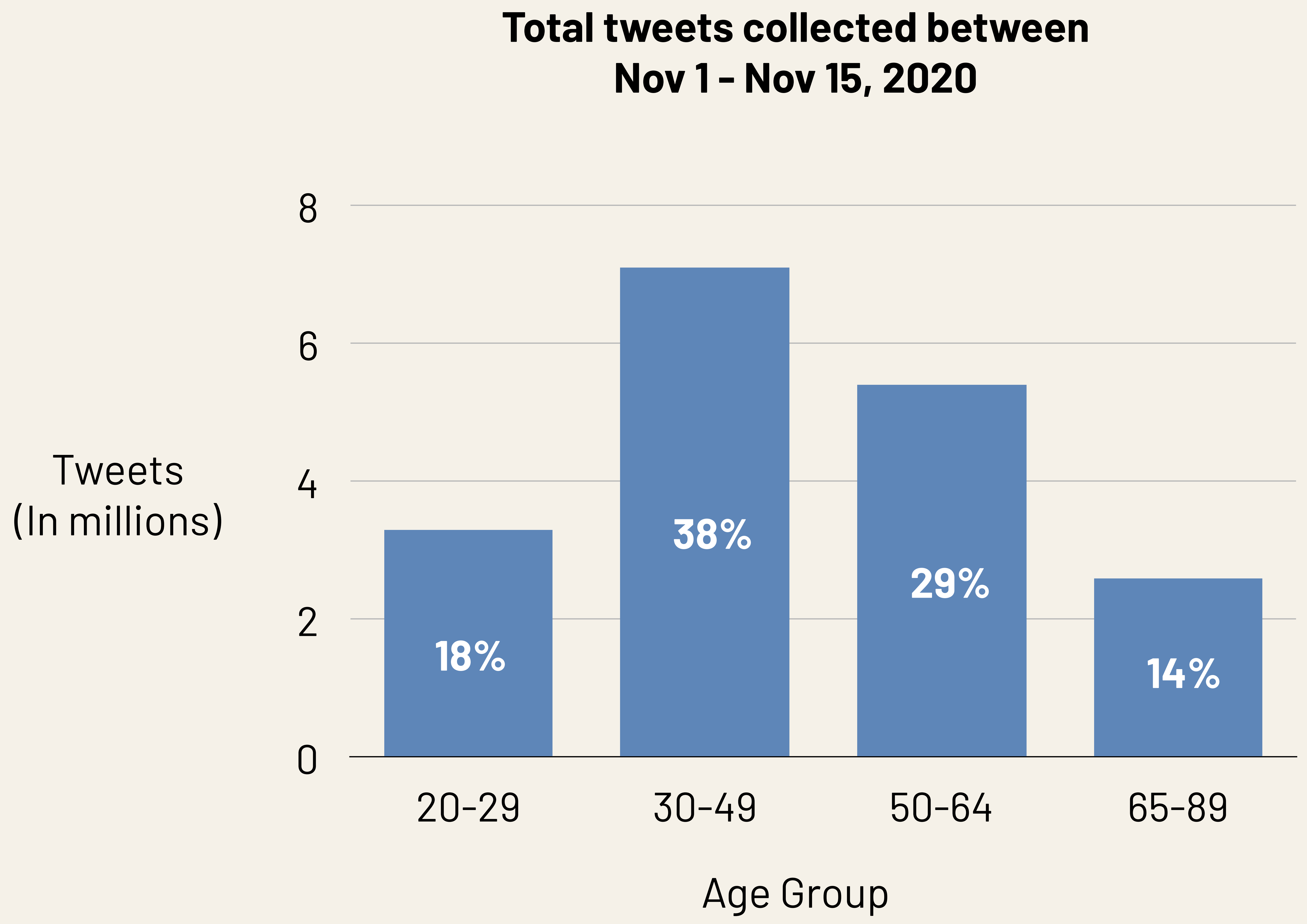
- ➡ Stratify sample by age



Method

Step 1: Use an initial keyword classifier to take an informed sample for hand coding

Step 2: Hand code 16,245 tweets for election relevance

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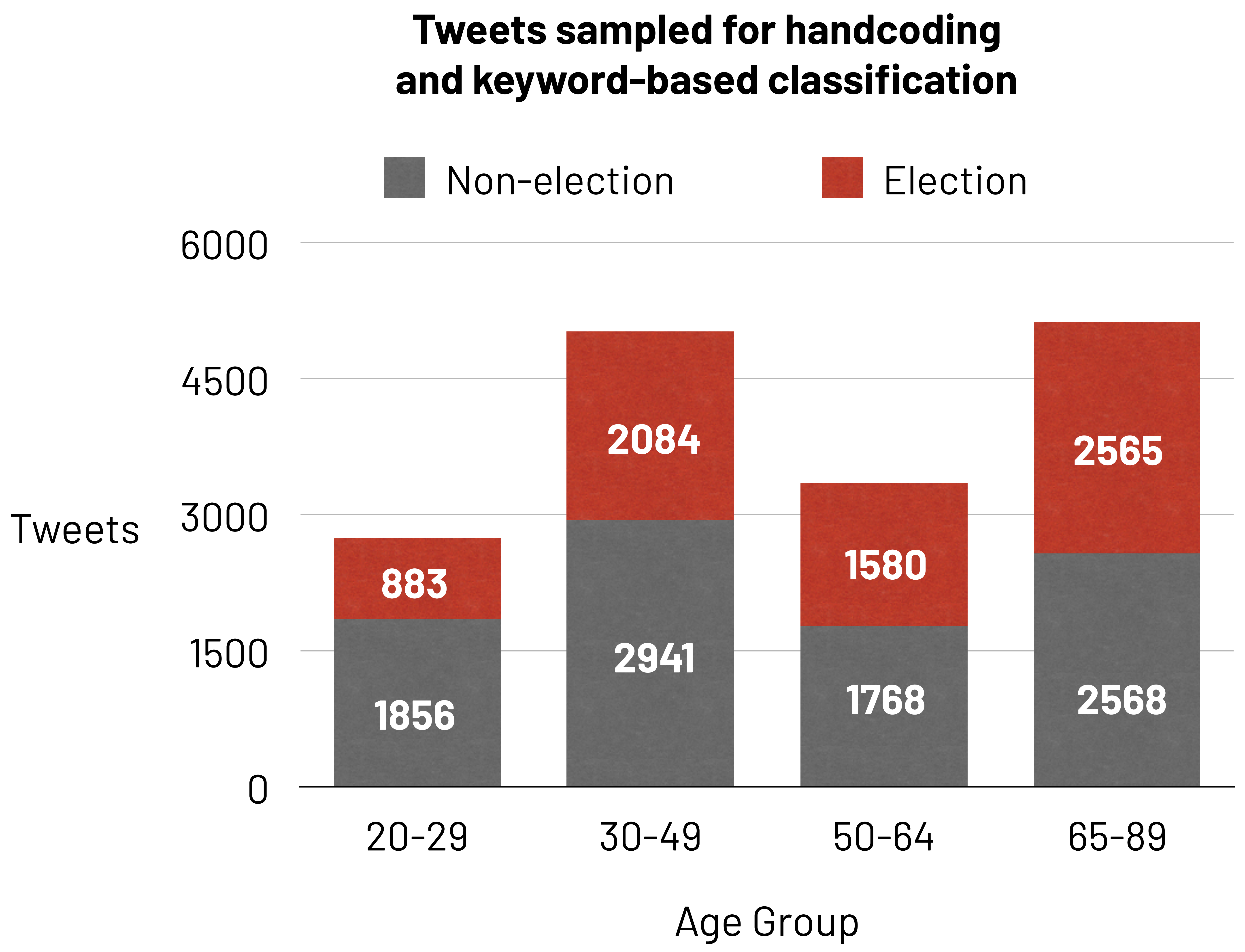

Keyword Classifier Accuracy

How frequently did the keyword classifier disagree with our handcoding?

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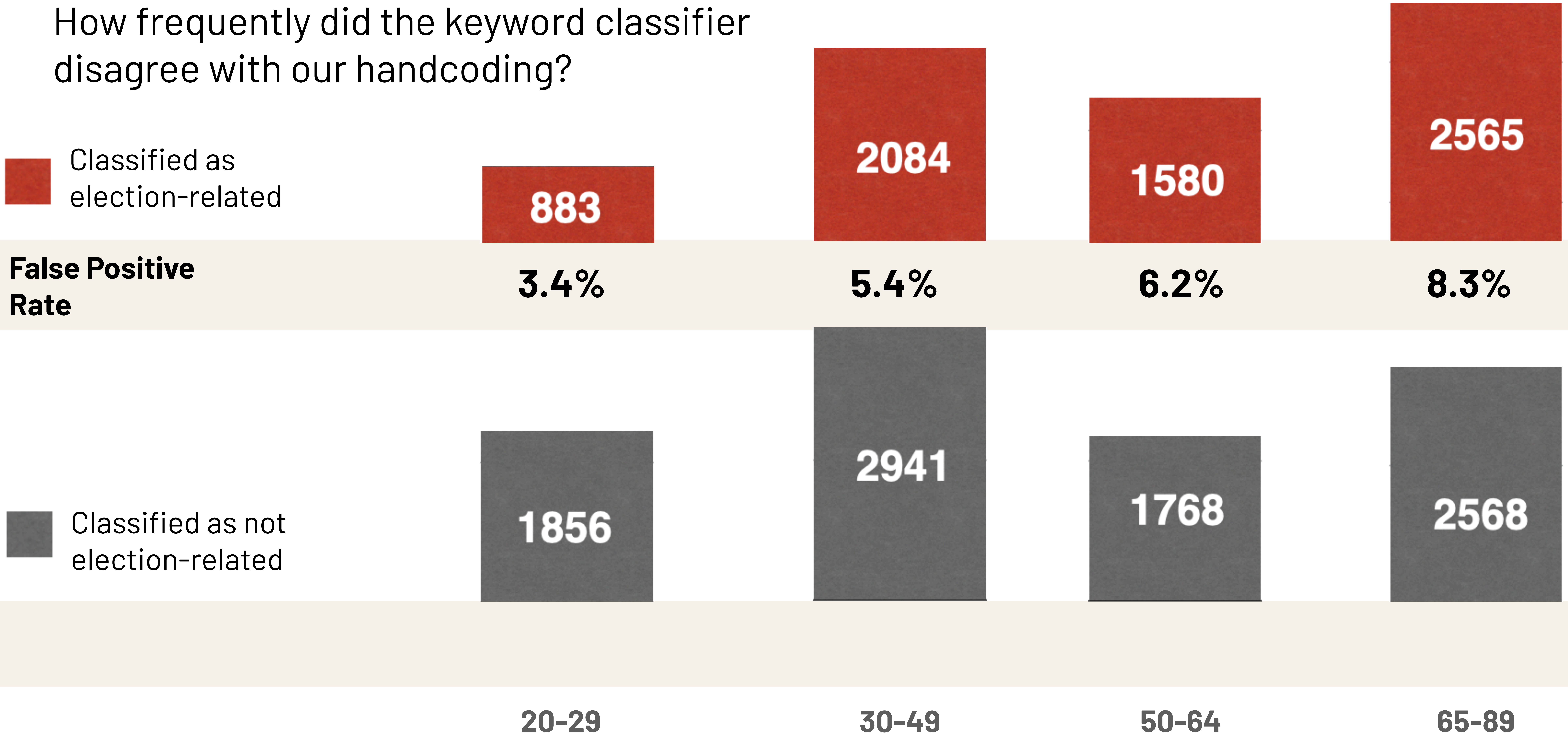

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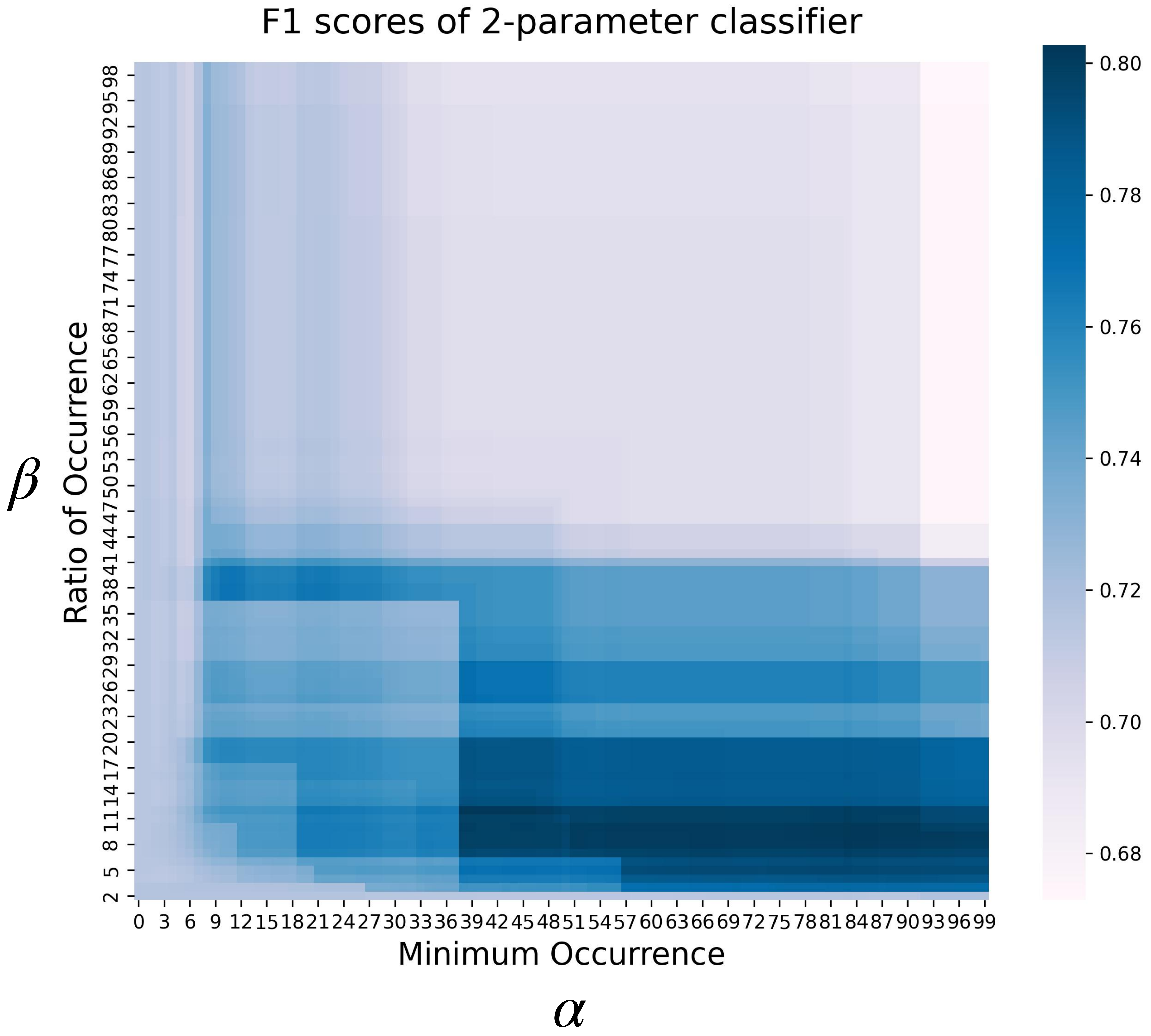

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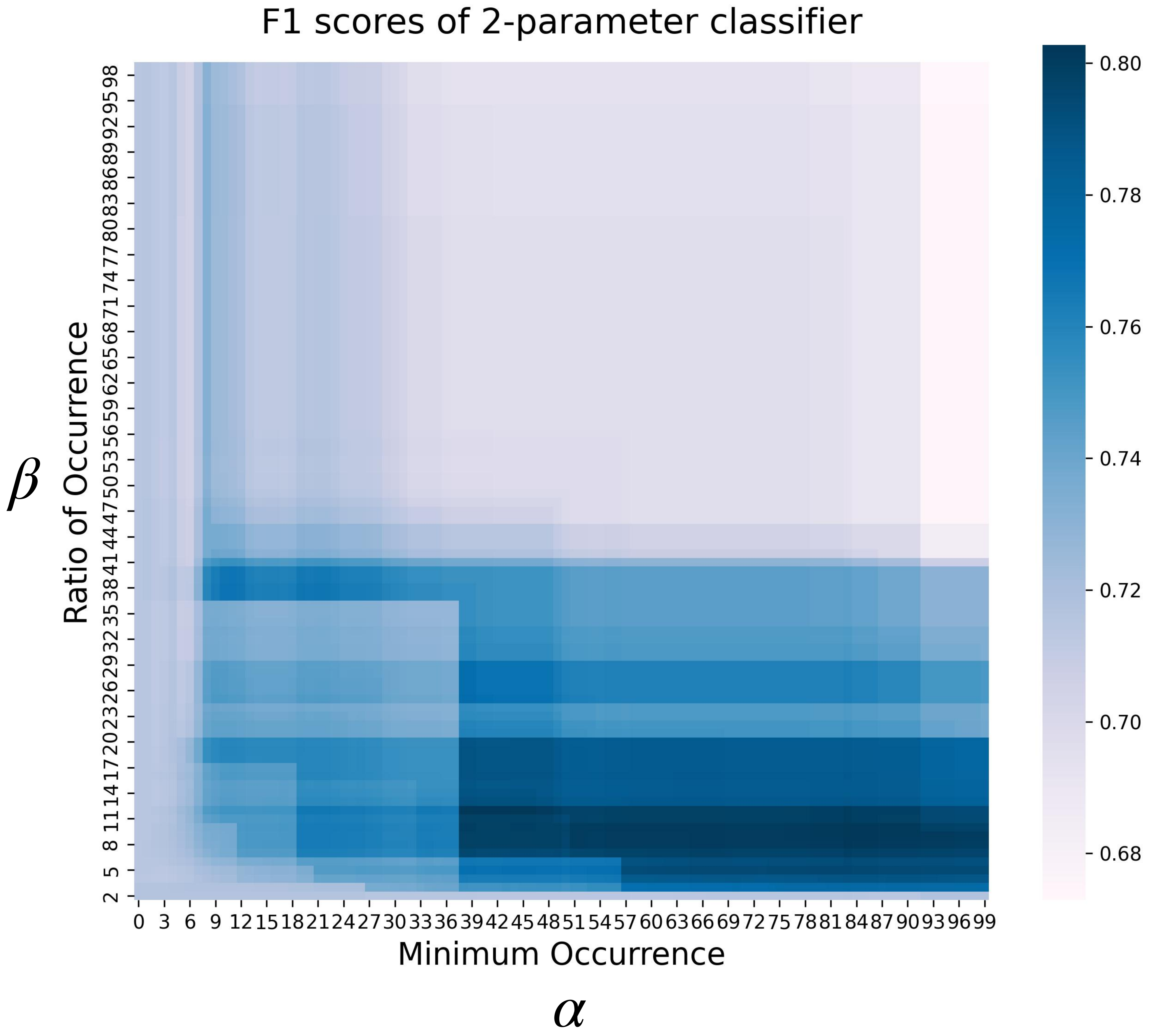
- Test 10,000 potential classifiers through a two-parameter model



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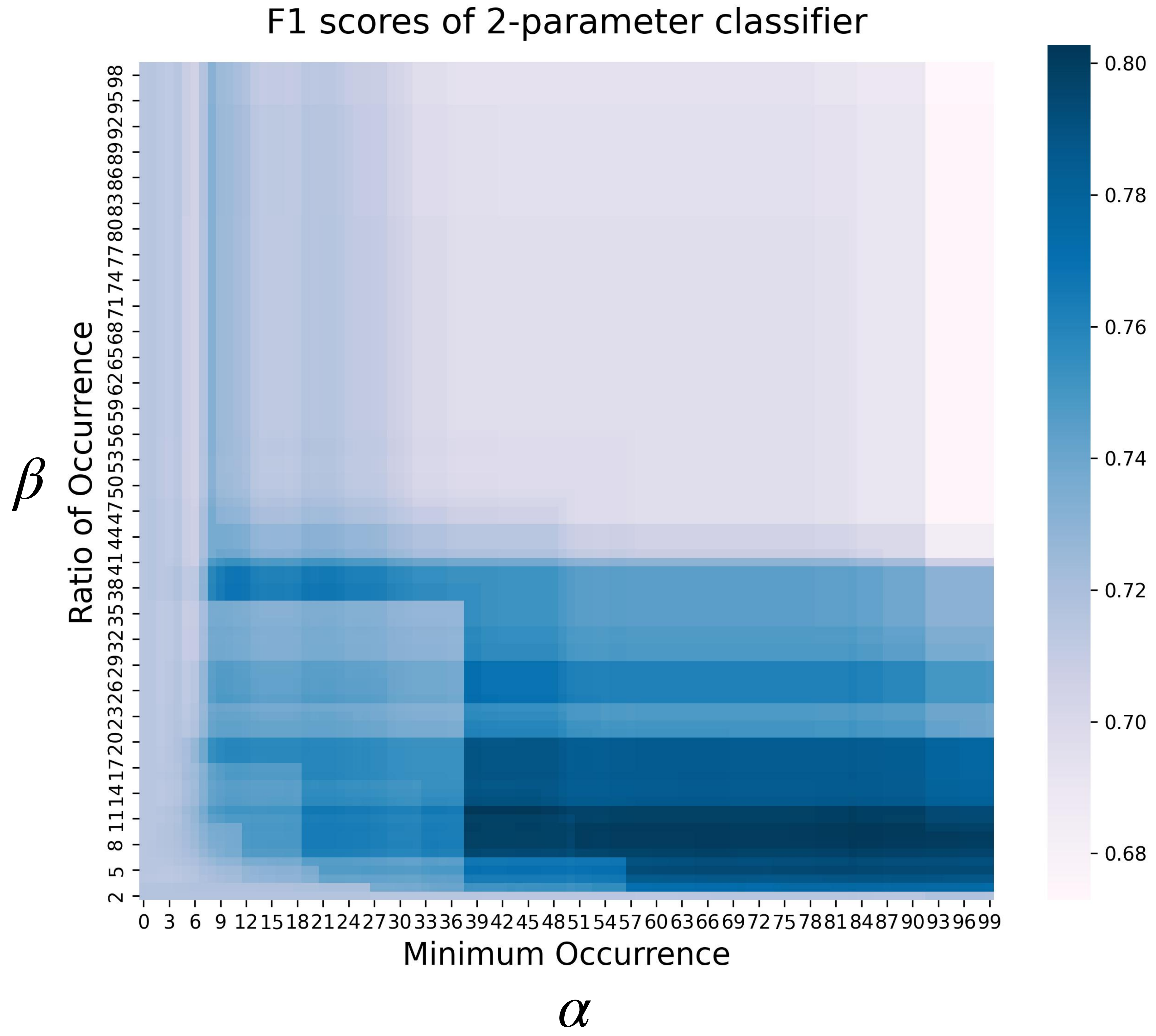

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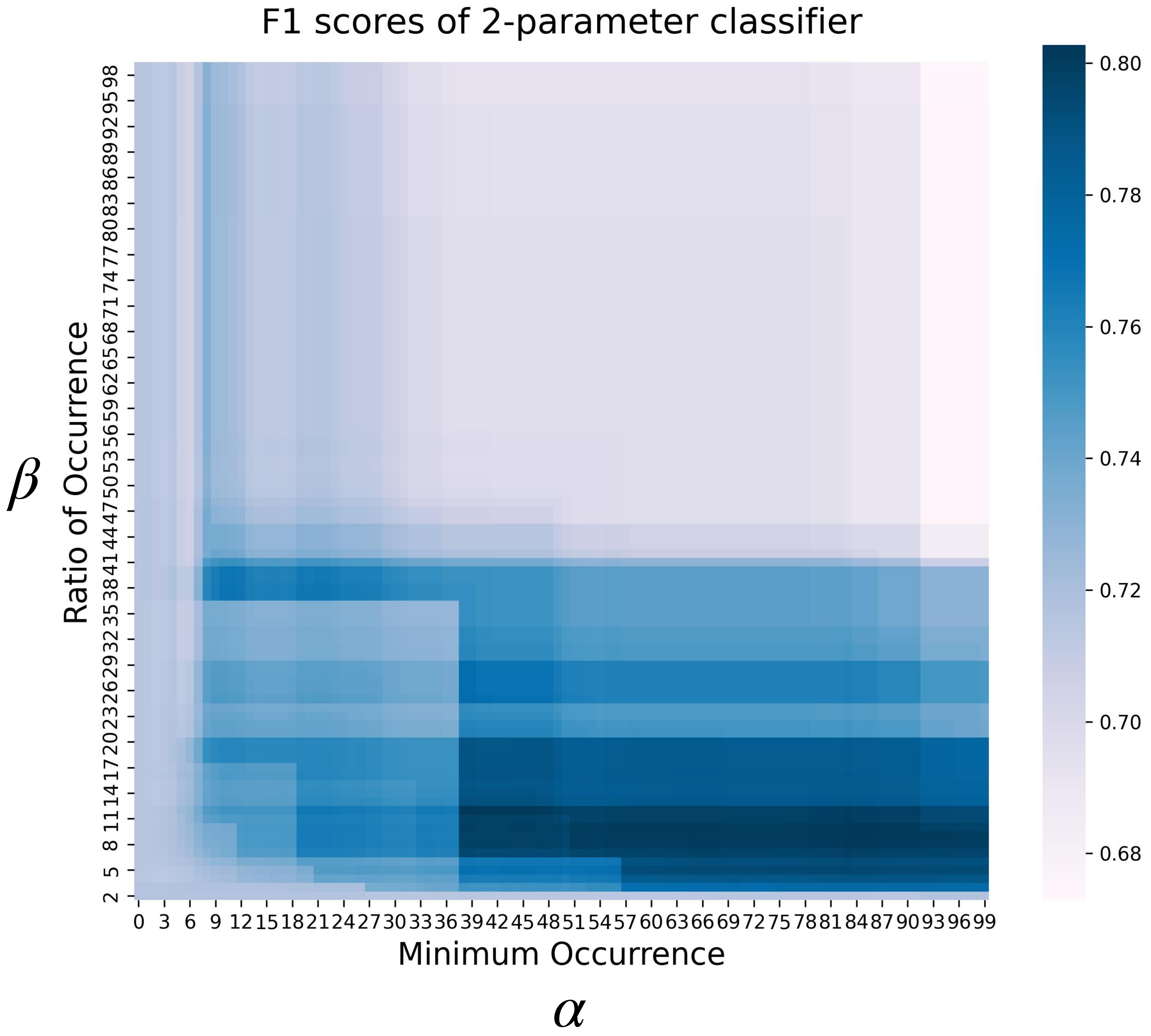

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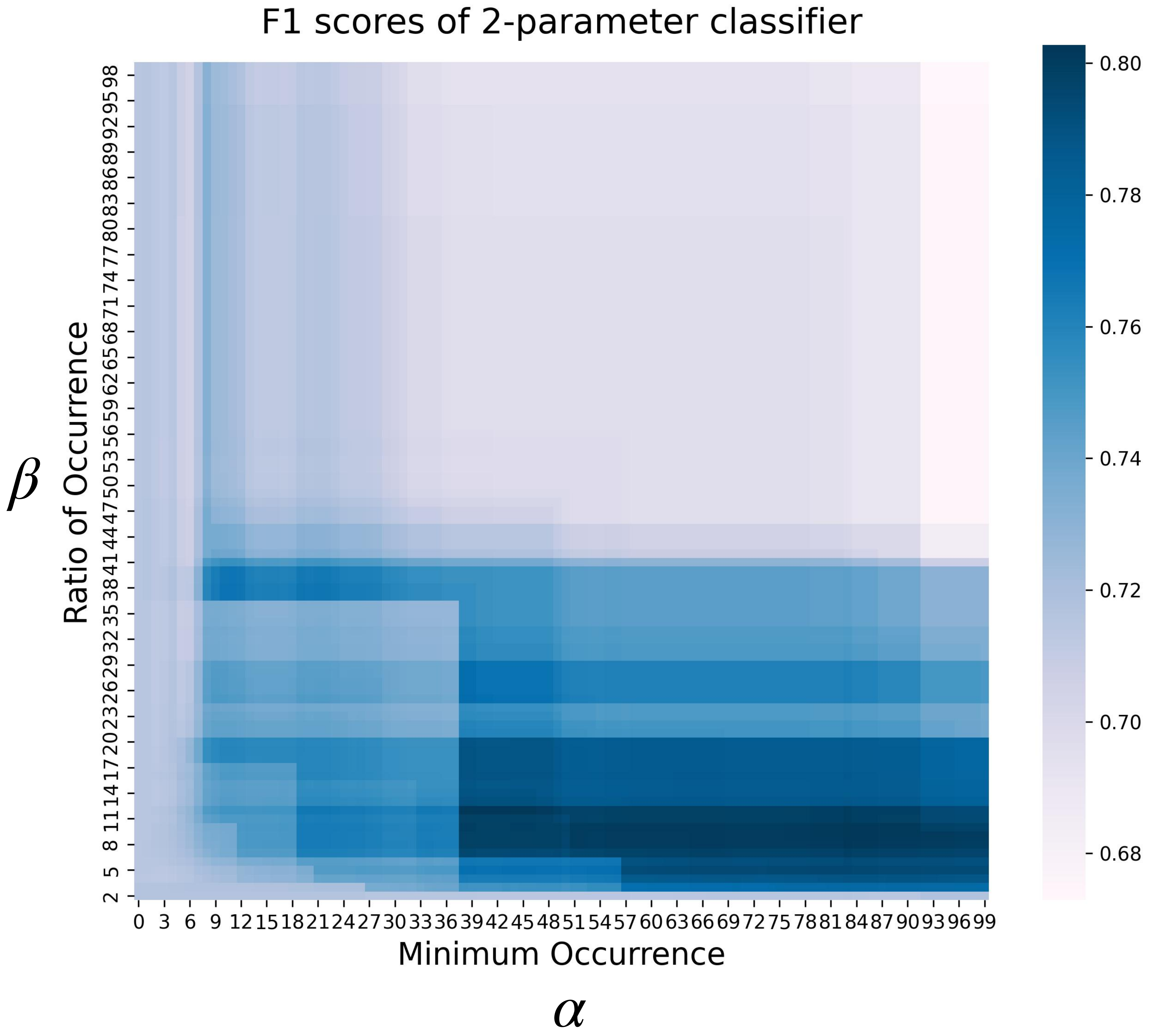

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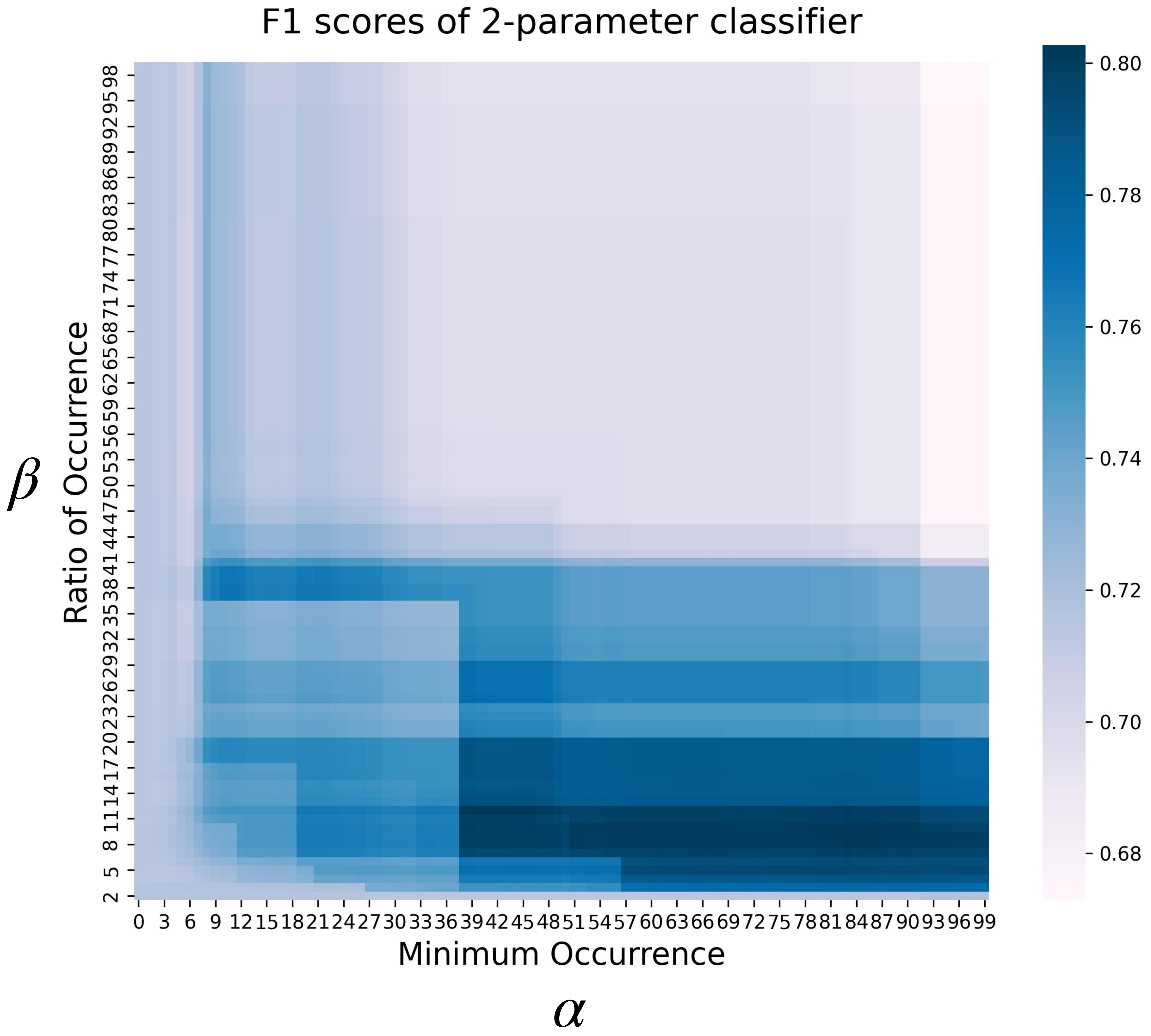

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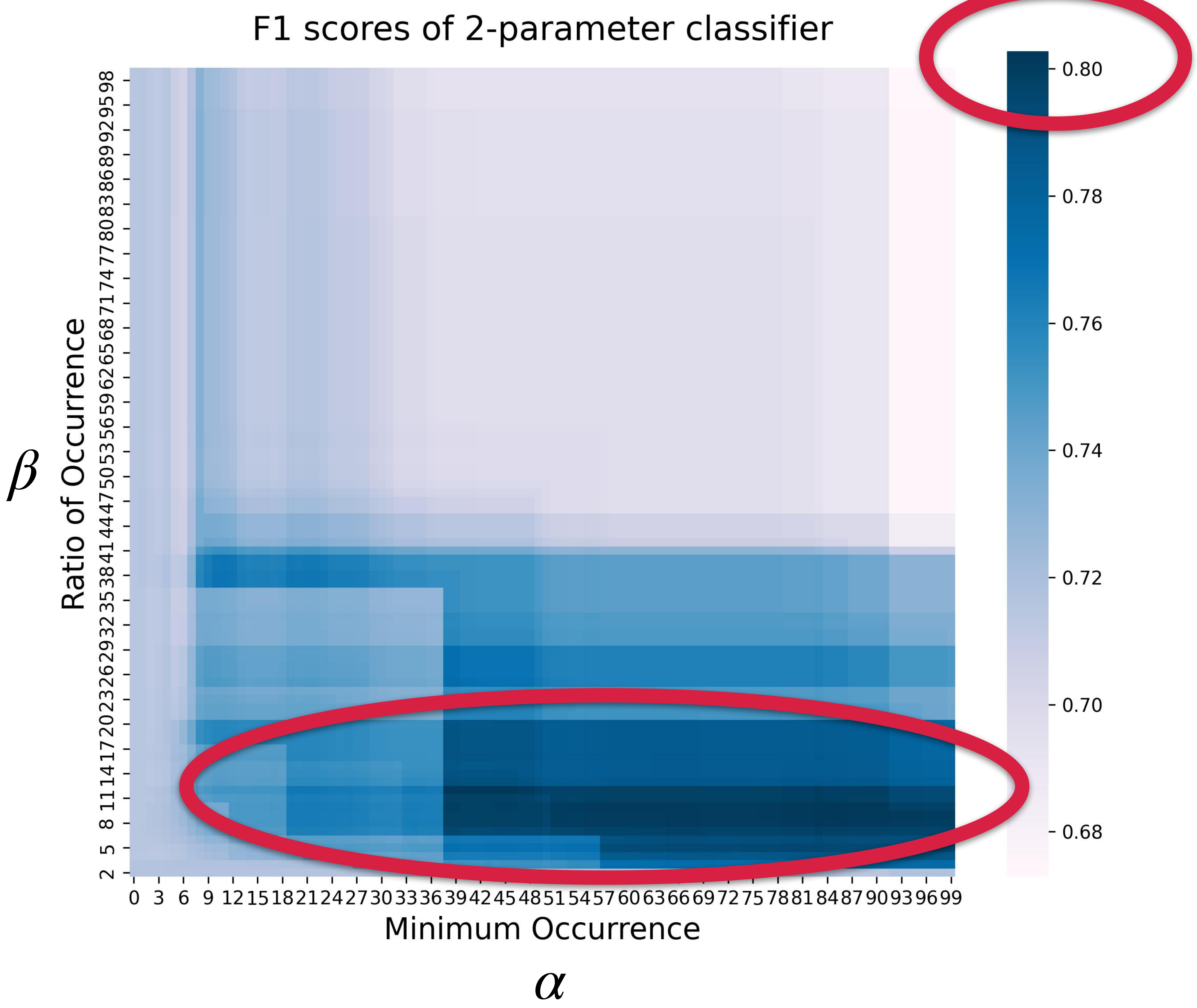
- Best models achieved (only) an F1-score of ~ 0.8



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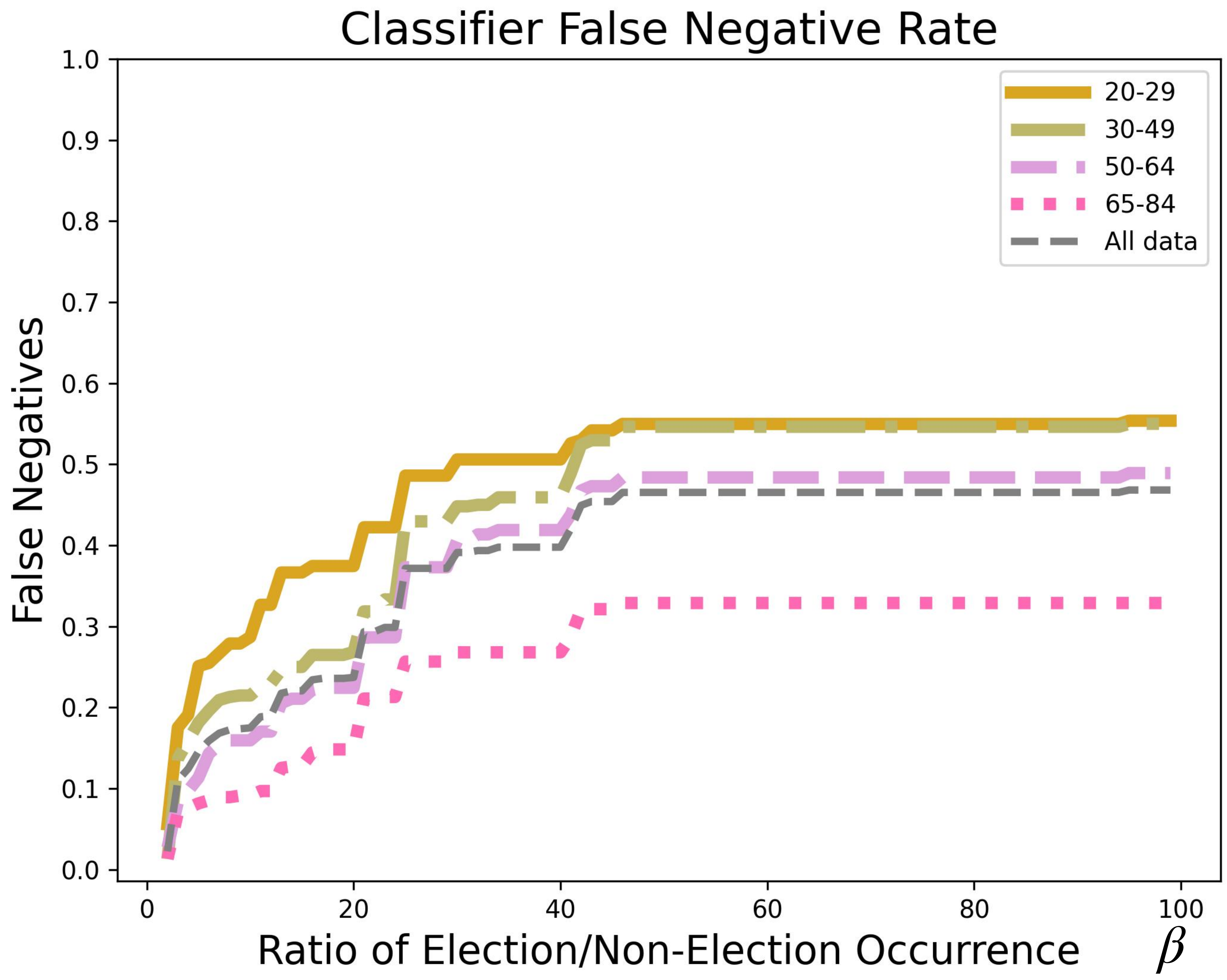

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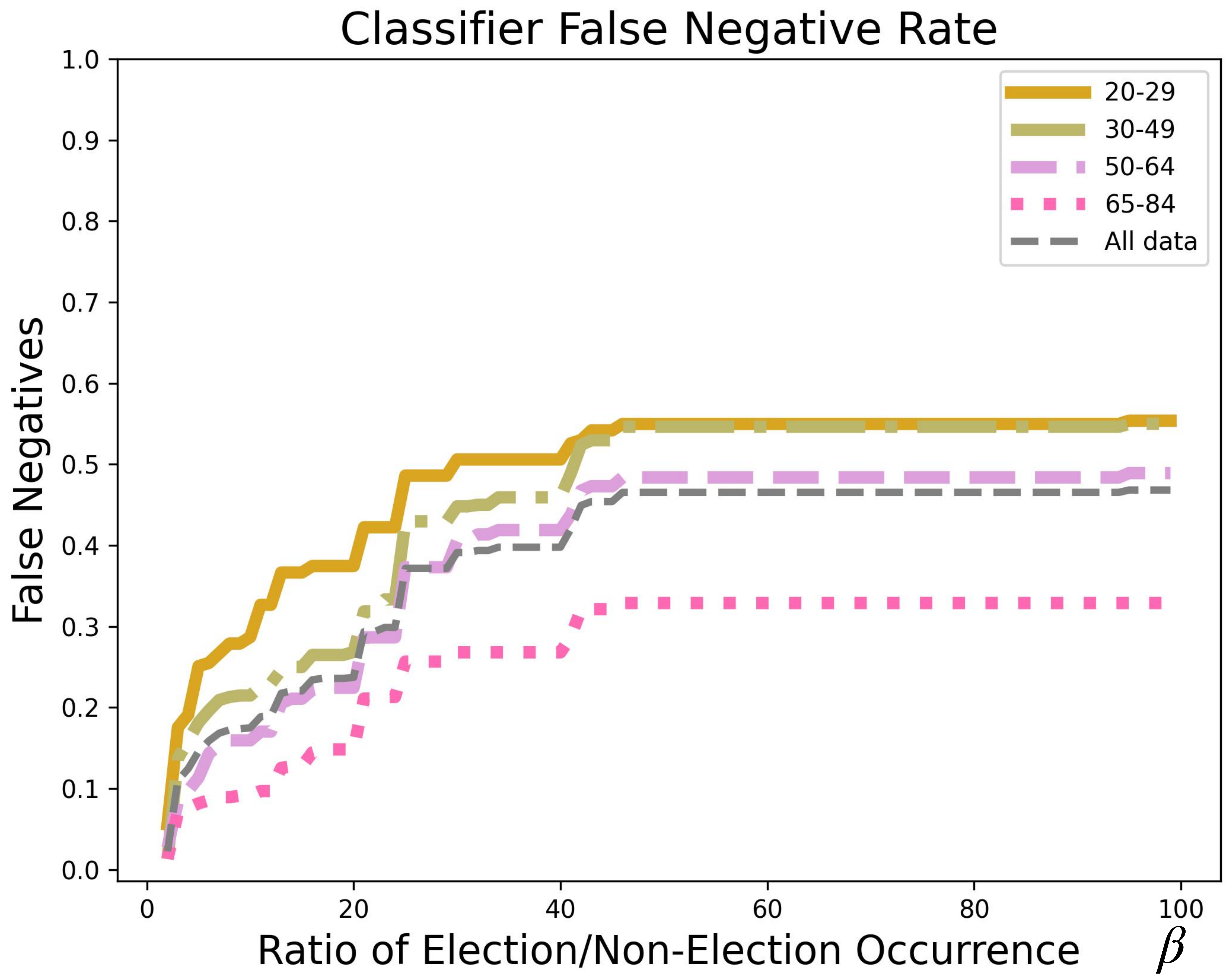

Older users consistently have fewer of their election tweets misclassified

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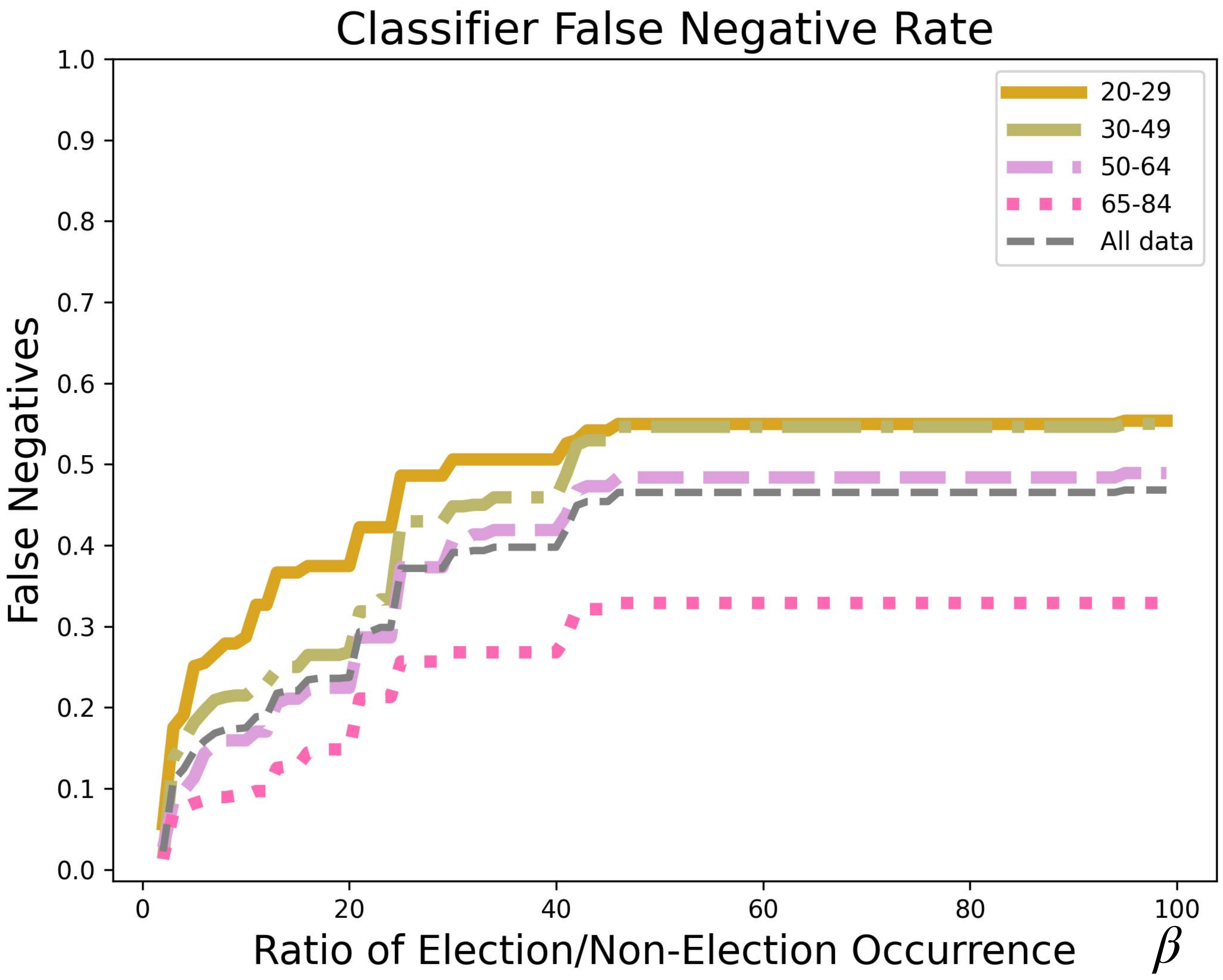
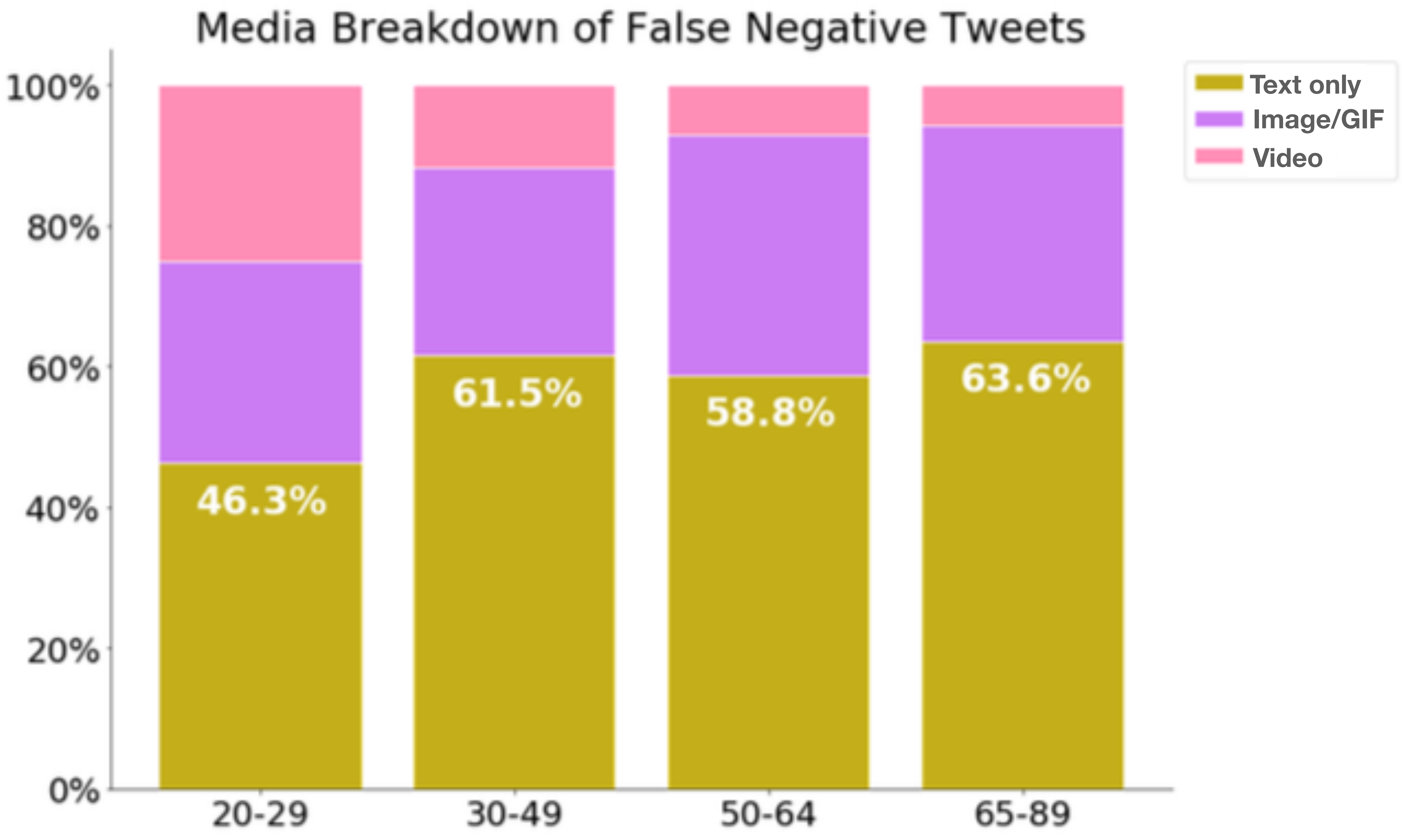


Younger users consistently have more of their election tweets misclassified

Older users consistently have fewer of their election tweets misclassified

Generational Trends?

Younger users frequently communicate using non-textual media, so keyword classifiers may underrepresent their political speech



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- How we measure "speech" has implications for whose speech we capture

- Matched panel data can help us interrogate these measurement biases
    - Have meaningful "negative" samples (eg, all users' posts)
    - Have age and other demographic info, can compare impact across categories

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- How we measure "speech" has implications for whose speech we capture
- Matched panel data can help us interrogate these measurement biases
  - Have meaningful "negative" samples (eg, all users' posts)
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Thank you!

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