Author Profiling

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Bots and Gender Profiling @ PAN - Authorship

- Given a Twitter feed, determine whether its author is a bot or a human. In case of human, identify her/his gender.

- More info about active tasks at https://pan.webis.de/clef19/pan19-web/

Bots and Gender Profiling @ Dataset

- 4120 english Twitter users with a feed of 100 tweets per user
  - 2060 bots - 50%
  - 1030 female - 25%
  - 1030 male - 25%

- Train - 80%
  - 1648 bots - 50%
  - 824 female - 25%
  - 824 male - 25%

- Test - 20%
  - 412 bots - 50%
  - 206 female - 25%
  - 206 male - 25%

Bots and Gender Profiling @ Dataset

- 3000 spanish Twitter users with a feed of 100 tweets per user
  - 1500 bots - 50%
  - 750 female - 25%
  - 750 male - 25%

- Train - 80%
  - 1200 bots - 50%
  - 600 female - 25%
  - 600 male - 25%

- Test - 20%
  - 300 bots - 50%
  - 150 female - 25%
  - 150 male - 25%

Bots and Gender Profiling @ Can you guess?

1. Imagine if Giroud went back to Arsenal. That would be fantastique. Will be talking about some new Irish tunes at 7:30pm on @theirishjam this evening! https://t.co/oqFnoApCV9 *Incredibly..... I can't see properly through my glassy eyeballs. So happy for Giroud. Incredible sad for Modric. Hate Griezmann even more. France could end their twenty year wait to reclaim the title Les Pimps, but Croatia could get their first World Cup honour. So conflicted about who I want to win today. I love Giroud but now I also love Modrić. I have Croatia in a sweepstakes and could win big coin, however Giroud could win a World Cup medal...

Bots and Gender Profiling @ Can you guess?

2. Women's marches protest #DonaldTrump on anniversary of inauguration – live #WomansMarch Community campaign... RT @ruth_hunt: 40% of #trans people have experienced hate crime in the last 12 months. 40%. Trans people are facing unprecedented levels of... RT @jeremycorbyn: Very important report by @StonewallUK about the discrimination and harassment trans people face every day. We must all do... RT @FrancesOGrady: Shocked by today's @stonewalluk report, showing that trans workers still face bullying, harassment and even physical vio... @jeremycorbyn on #Carillion: we'll

Bots and Gender Profiling @ Can you guess?

3. @KidrauhlsFredoo just saying he always looks like that with fans, so it's not a new look, lol @KidrauhlsFredoo he is always like that with fans.. Would you #FitchTheHomeless? #JustinBieber is hiking #Belieber #Beliebers #jb #hiking #haveaniceday RT @OMGtrolls: O.O RT @AhoyBieber: Awwww but that is cute is sang for fans from the roof of his hotel. Justin's original idea to release music has gone out the window, That was Justin's was if releasing music differently, u srs scooter? No one love like we do @biebersvideo: i'm not hating on scooter. i'm just disappointed of him. She's been my idol since day 1. She's worked so hard! #votearianagrande http://t.co/EPyBDwm22L RT @marucosu1919: ❤️RETWEET ❤️ IF ❤️ YOU ❤️ FOLLOW ❤️ BACK❤️ #TeamFollowBack #TFBJP #followme #ifollownGain #TeamFollowWack #autofollowback #foll… I was stupid and you're the best dad in the world RT @elaph1421: I feel very bored

Bots and Gender Profiling @ Can you guess? Truths

1. female
2. male
3. bot

Bots and Gender Profiling @ A first aproach

First of all we analyzed the tweets with a preselected list of features like

- number of words
- number of characters
- average word len
- number of tags
- number of hashtags
- readability

Bots and Gender Profiling @ A first aproach

- number of words
- number of characters
- average word len
- number of stop words
- number of tags
- number of hash tags
- readability
- number of digits
- number of secure links
- number of unsecured links
- number of percent
- number of exclamation marks
- number of ampersands
- number of question marks
- number of commas
- number of points
- number of emoji
- number of tildes
- number of dollars
- number of circumflex accents
- number of stars
- number of parenthesis
- number of minuses
- number of underscores

Bots and Gender Profiling @ A first aproach

- number of equals
- number of pluses
- number of brackets
- number of curly brackets
- number of vertical bars
- number of semicolons
- number of colons
- number of apostrophes
- number of grave accents
- number of quotation marks
- number of slashes
- number of less grater than signs
- number of words in bot popular words
- number of words in human popular words
- number of words in male popular words
- number of words in female popular words
- number of words in bot human popular words
- number of words in human bot popular words
- number of words in male female popular words
- number of words in female male popular words
- number of different words

Bots and Gender Profiling @ A first aproach Results

- english, overall: 82.9%
- spanish, overall: 72.8%

Bots and Gender Profiling @ String kernels*

- The kernel function gives kernel methods the power to naturally handle input data that are not in the form of numerical vectors—for example, strings.

- The kernel function captures the intuitive notion of similarity between objects in a specific domain and can be any function defined on the respective domain that is symmetric and positive definite.

*String Kernels for Native Language Identification: Insights from Behind the Curtains - R. T. Ionescu, M. Popescu, A. Cahill

Bots and Gender Profiling @ String kernels*

$$k_p(s,t) = \sum_{v \in \Sigma^p} \text{num}_v(s) \cdot \text{num}_v(t)$$

$$k_p^{0/1}(s,t) = \sum_{v \in \Sigma^p} \text{in}_v(s) \cdot \text{in}_v(t)$$

$$k_p^{\cap}(s,t) = \sum_{v \in \Sigma^p} \min\{\text{num}_v(s), \text{num}_v(t)\}$$

*String Kernels for Native Language Identification: Insights from Behind the Curtains - R. T. Ionescu, M. Popescu, A. Cahill

Bots and Gender Profiling @ Our string kernel

$$k_p^{min/max}(s,t) = \sum_{v \in \Sigma^{\cap}} \frac{min\{num_v(s), num_v(t)\}}{max\{num_v(s), num_v(t)\}}$$

where $\Sigma^{\cap} = S \bigcap T$

Bots and Gender Profiling @ Our string kernel variations

$$k_p^{\sqrt{min/max}}(s,t) = \Sigma_{v \in \Sigma^{\cap}} \sqrt{\frac{min\{num_v(s), num_v(t)\}}{max\{num_v(s), num_v(t)\}}}$$

where $\Sigma^{\cap} = S \bigcap T$

Bots and Gender Profiling @ Our string kernel variations

$$k_p^{(min/max)^2}(s,t) = \Sigma_{v \in \Sigma^{\cap}} \left(\frac{min\{num_v(s), num_v(t)\}}{max\{num_v(s), num_v(t)\}} \right)^2$$

where $\Sigma^{\cap} = S \bigcap T$

Bots and Gender Profiling @ Tweaks

- We also did a normalization before we applied the kernel function.
- We took the number of pgrams and divided by the number of all pgrams (so we get frequencies).
- Since we did this, the values for a pgram is now in [0; 1] (so we modified the spectrum function: (1 + numv(s)) * (1 + numv(t)))

Bots and Gender Profiling @ Tweaks

So if we have a file x, another file x2 (that has the text from x twice) and x3: the value for presence is the same for any combination but for intersect and spectrum is not

Lets take a pgram that occurs once in x "qy"

Bots and Gender Profiling @ Tweaks

Classic way for intersect:

$k(x, 2x) = 1$

$k(x, 3x) = 1$

$k(2x, 3x) = 2$

Bots and Gender Profiling @ Tweaks

So the value is not the same, even though tis the same text multiple times

After normalization, the pgram have the same frequency in all 3 files so it becomes

$k(x,2x)=c$

$k(x,3x)=c$

$k(2x,3x)=c$

Where c is a constant (something like 0.001)

Bots and Gender Profiling @ Results

Results with K3 on English tweets

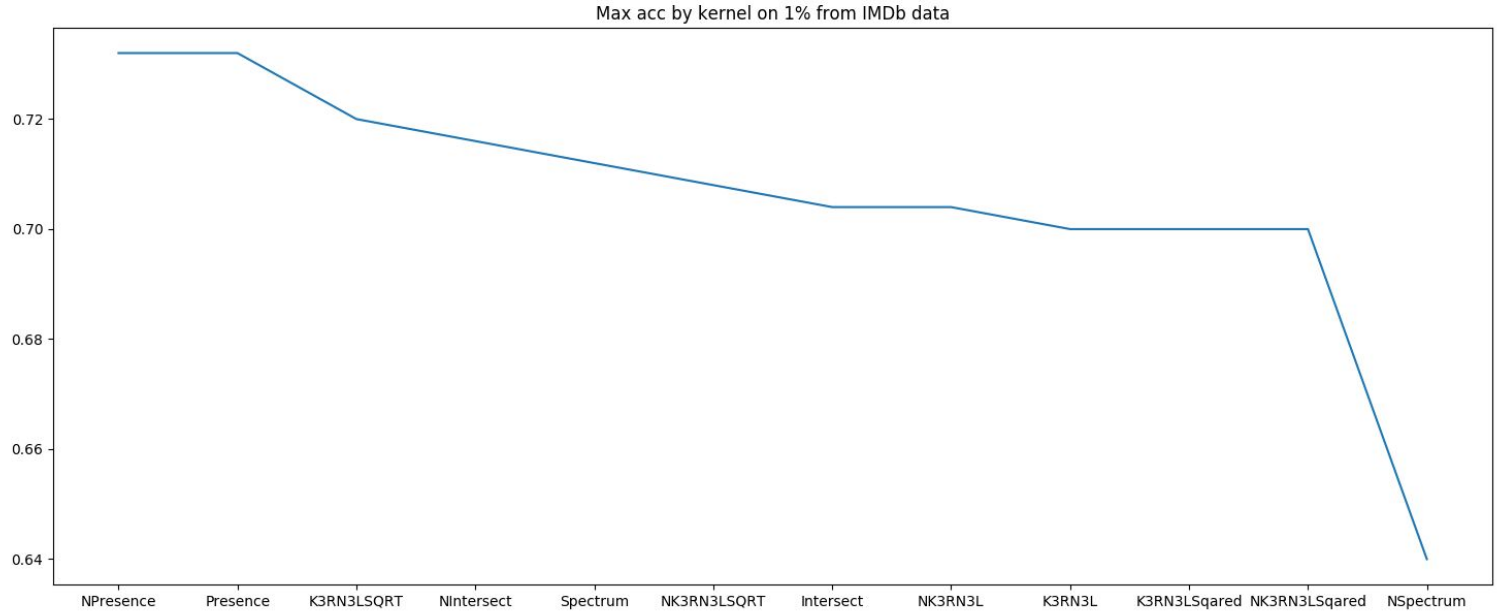
- **human/bot: 93.56%**
- **male/female: 81.82%**
- **overall: 87.69%**

Bots and Gender Profiling @ Results

Results with K3 on Spanish tweets

- **human/bot: 81.67%**
- **male/female: 68.89%**
- **overall: 75.28%**

Our string kernels vs others string kernels on a new task



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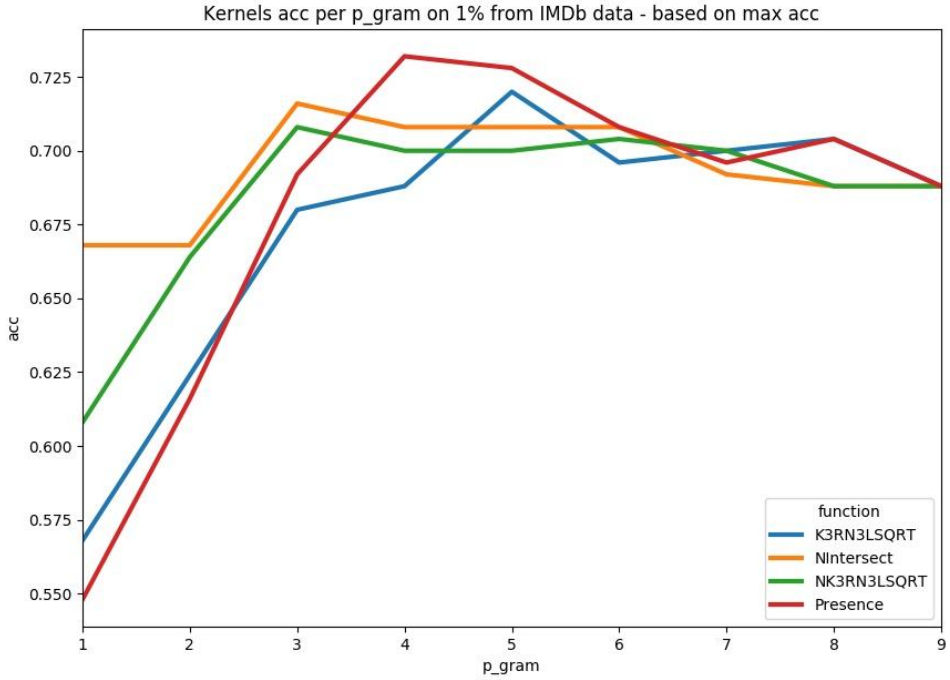

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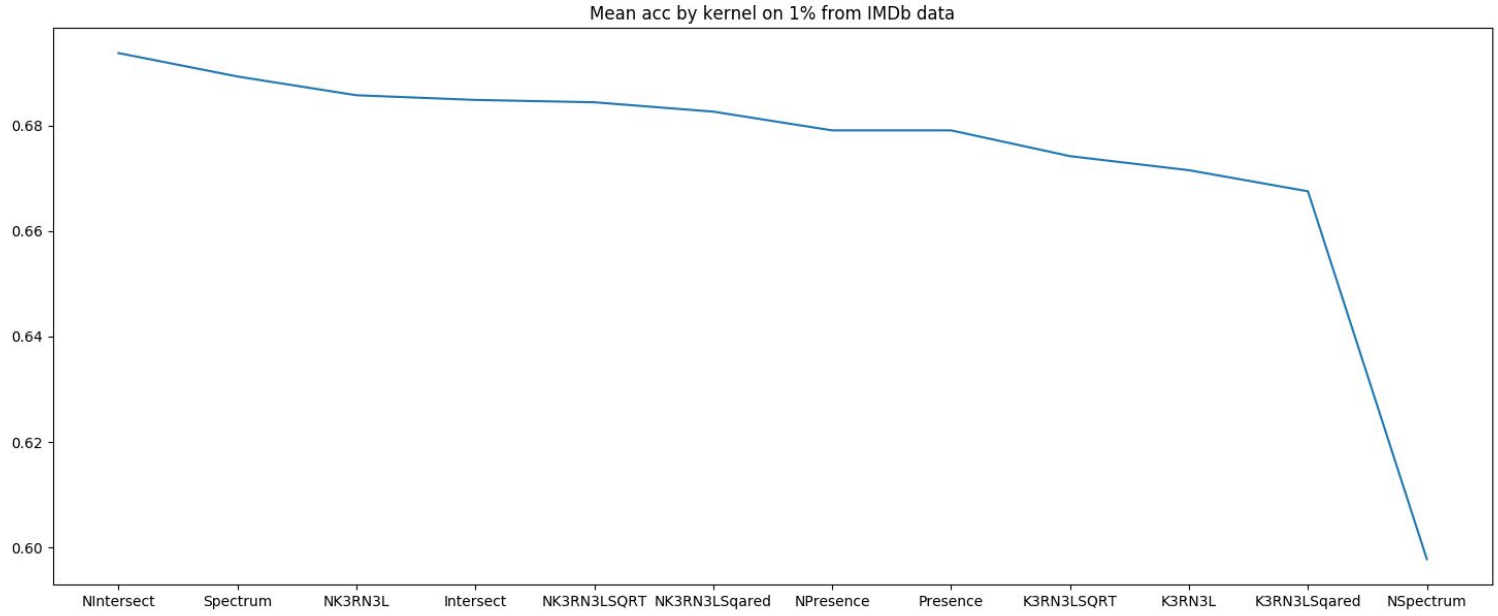

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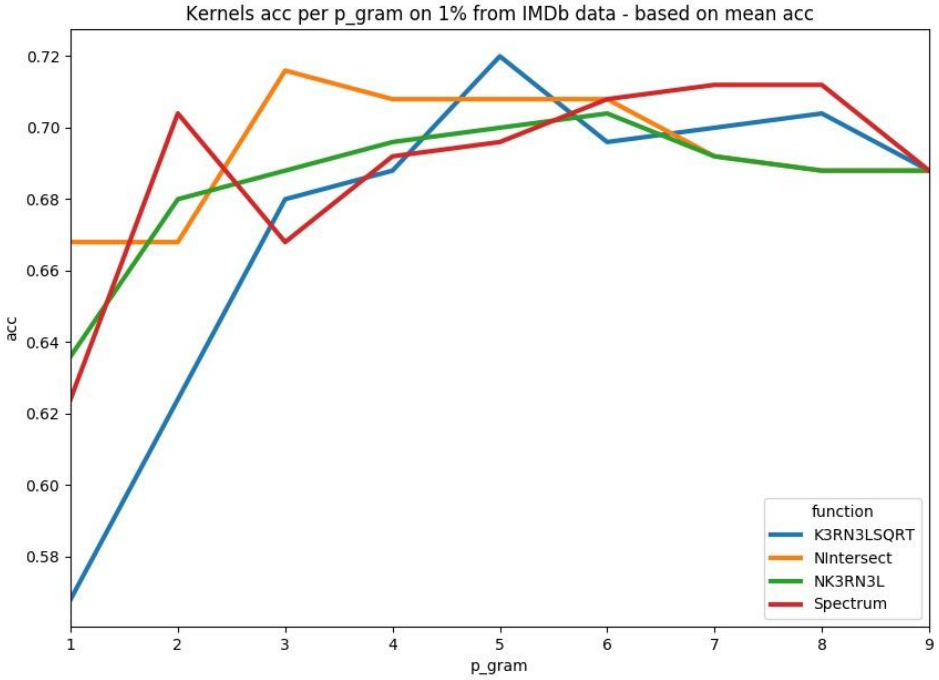

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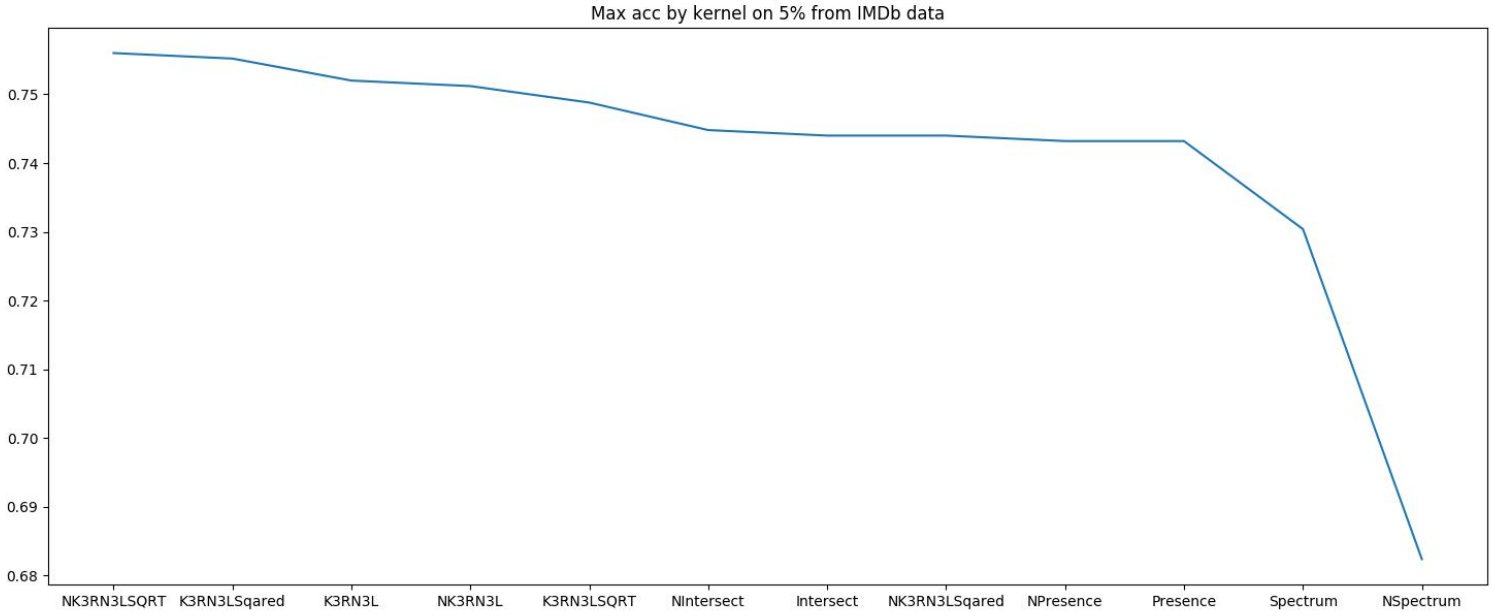

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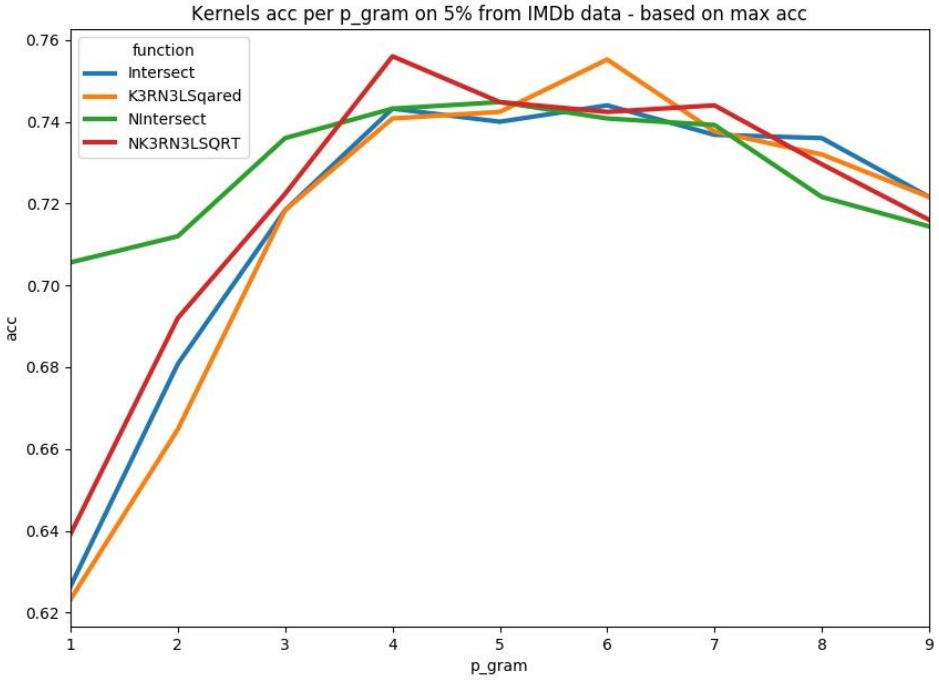

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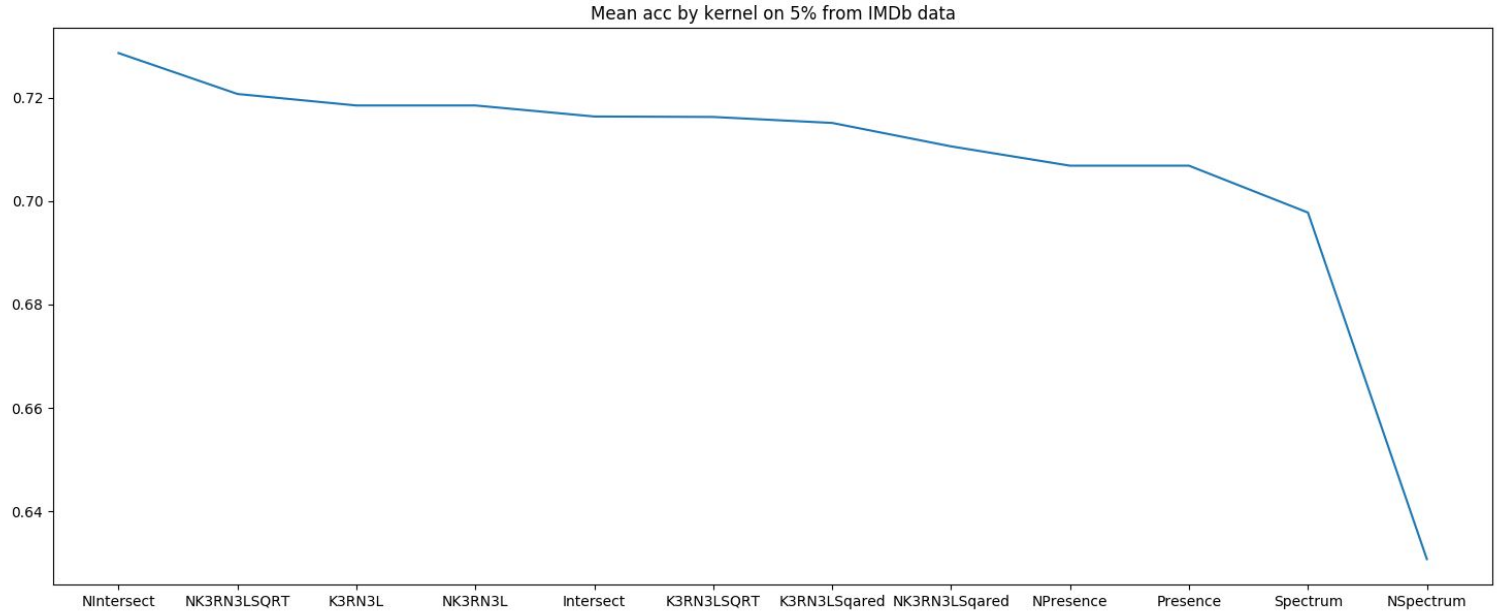

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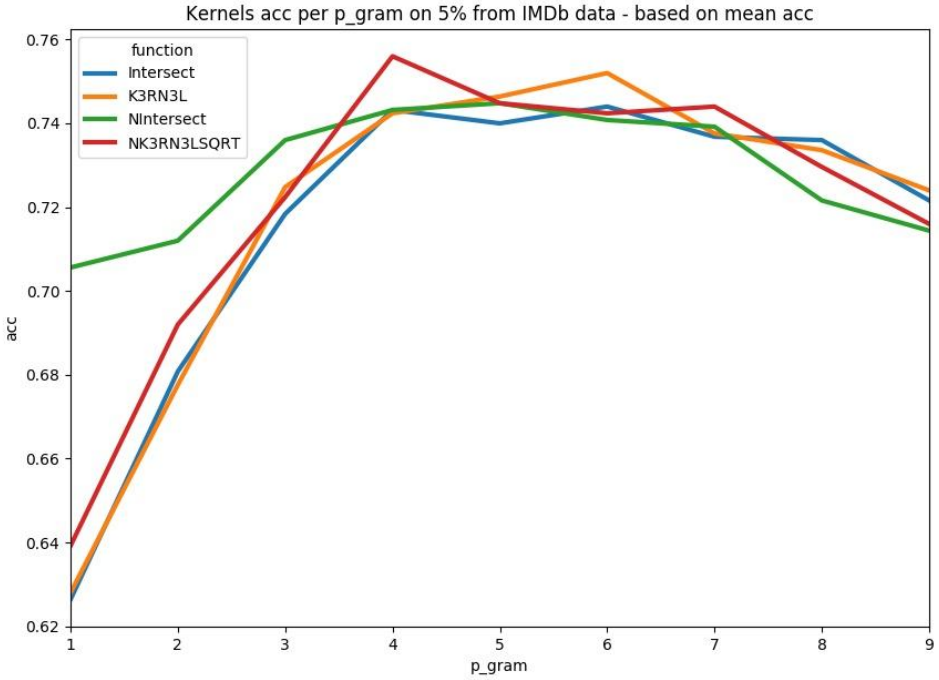

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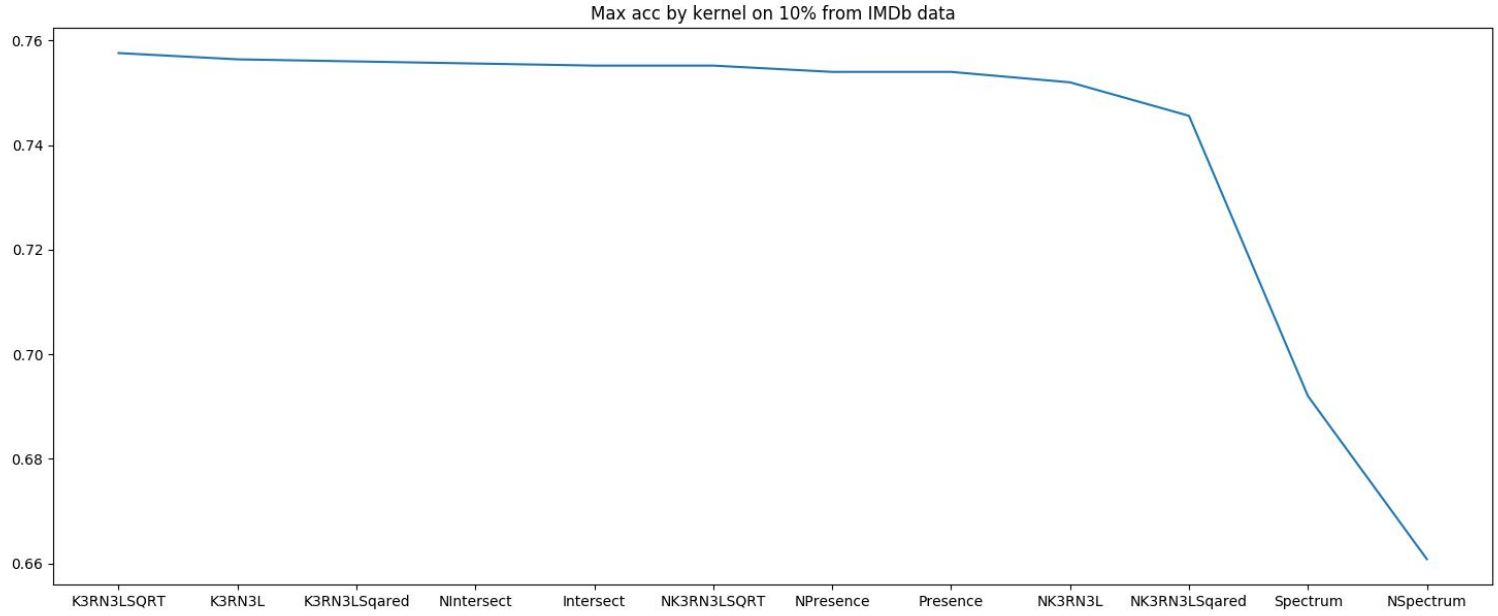

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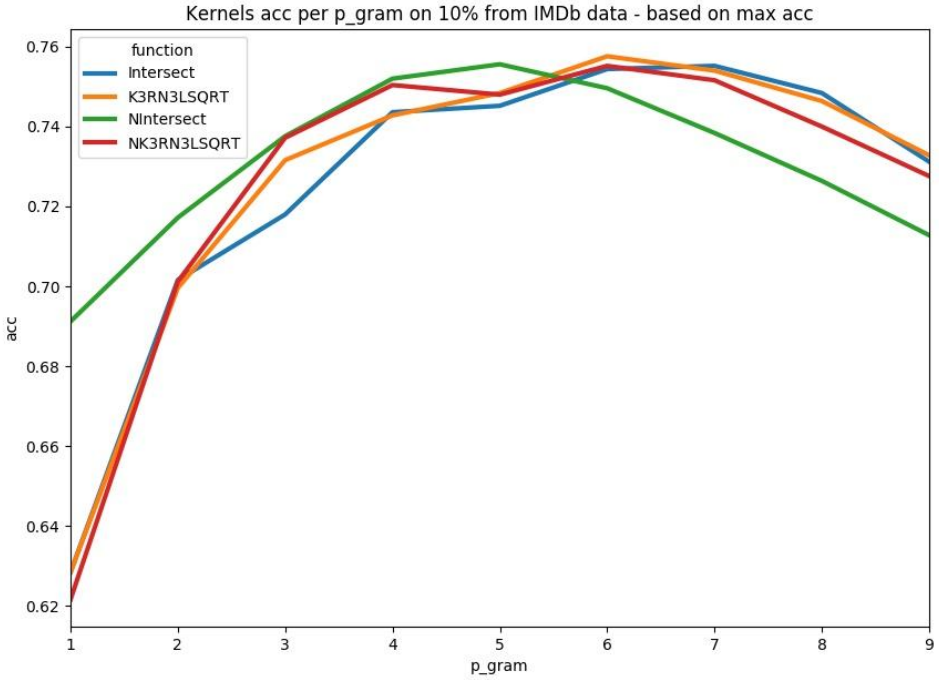

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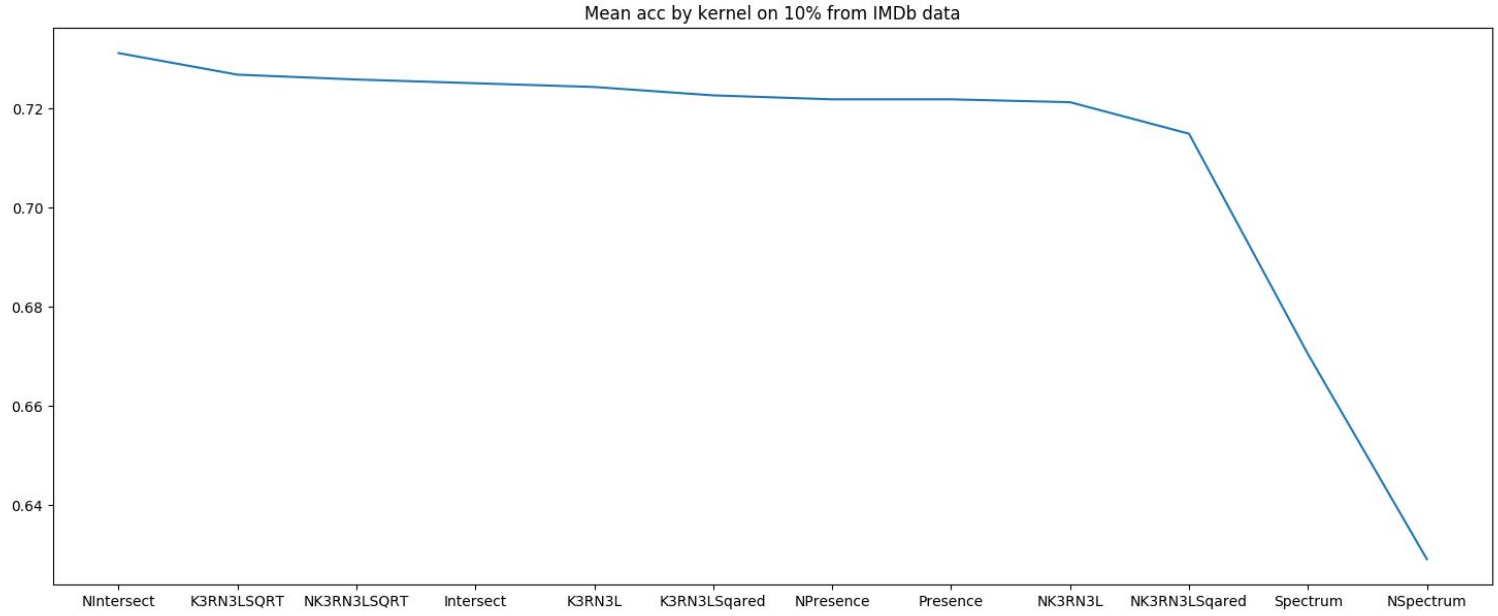

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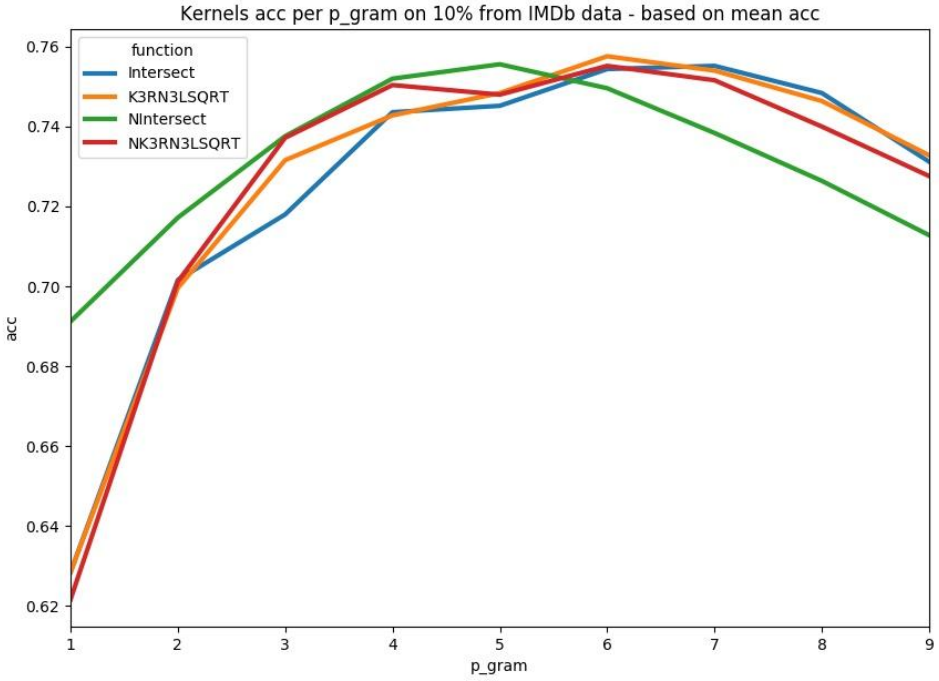

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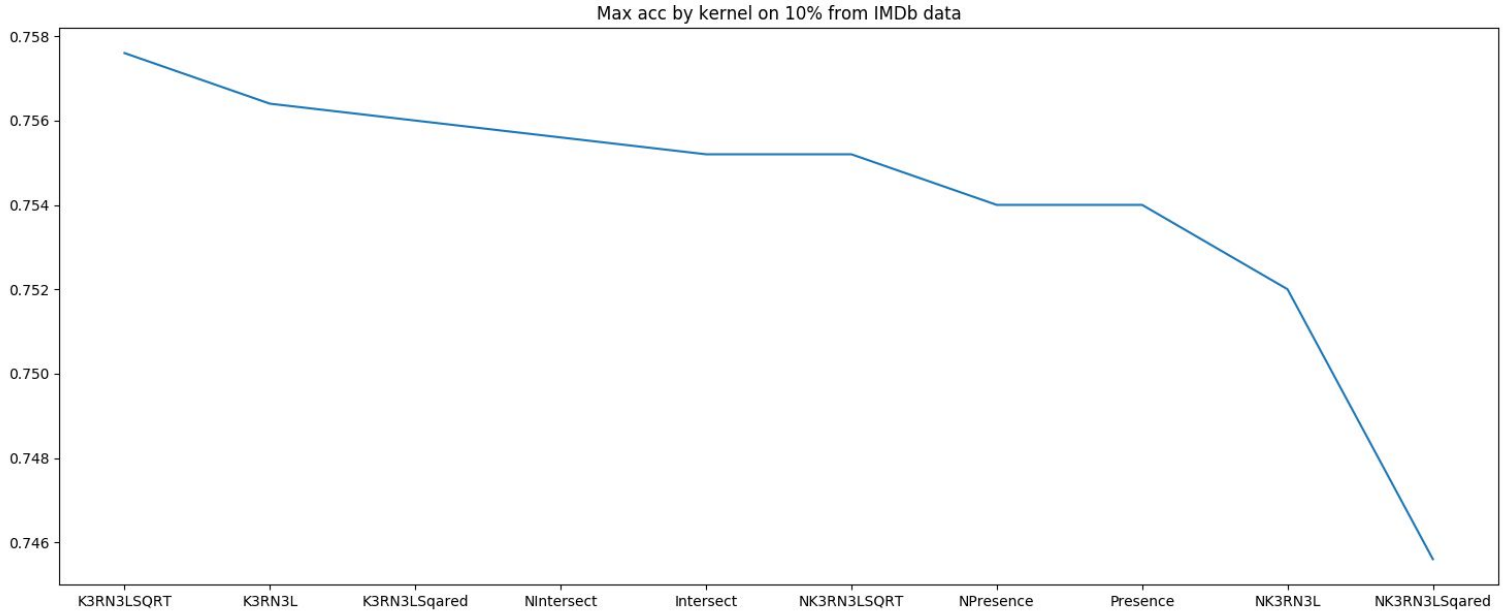

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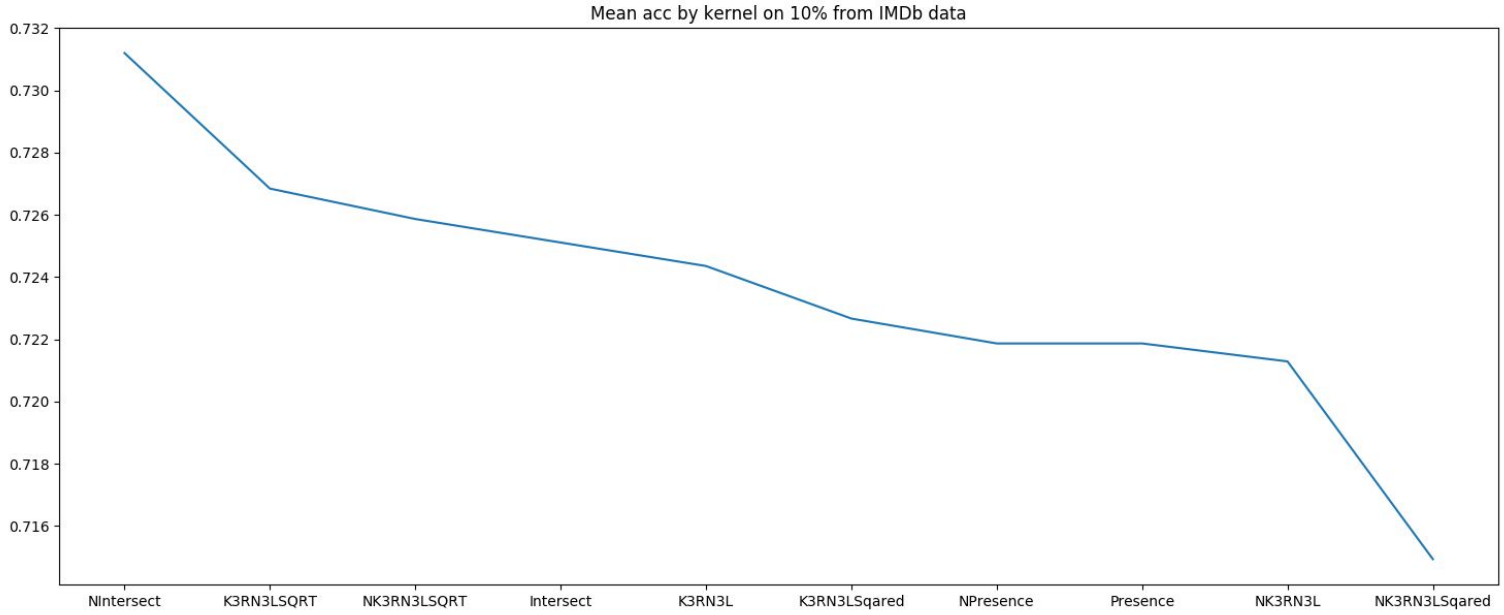

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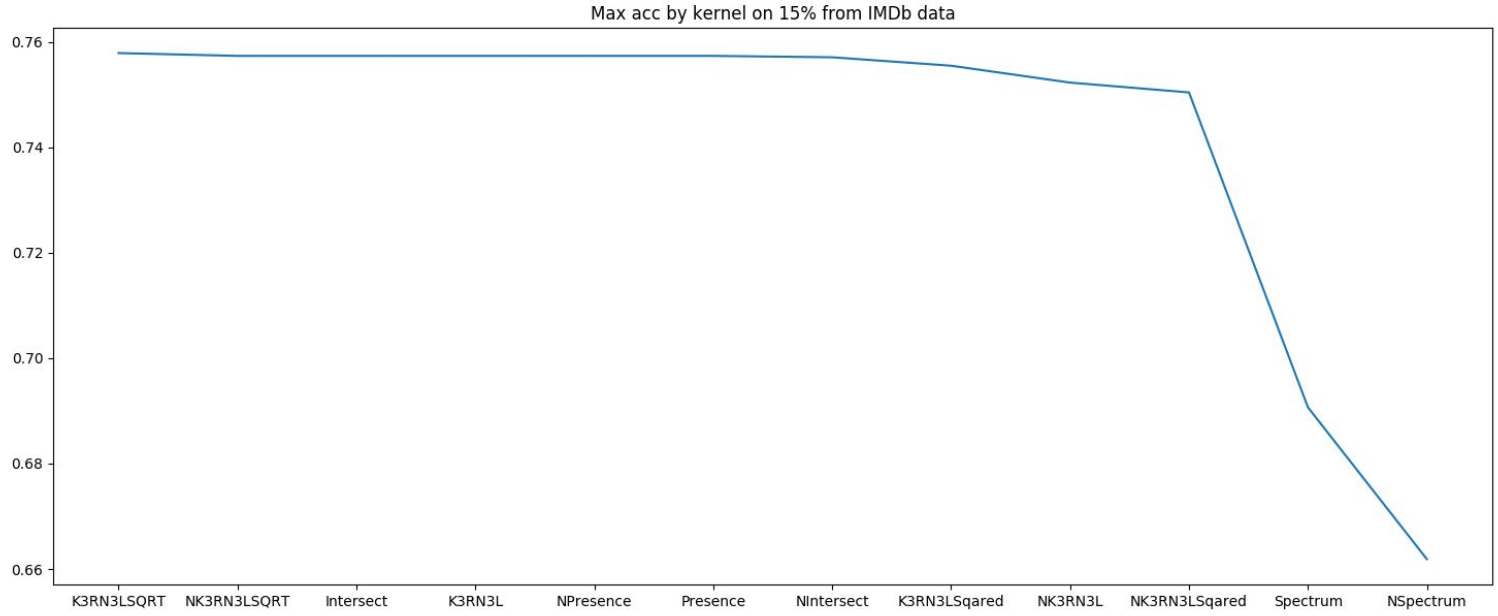

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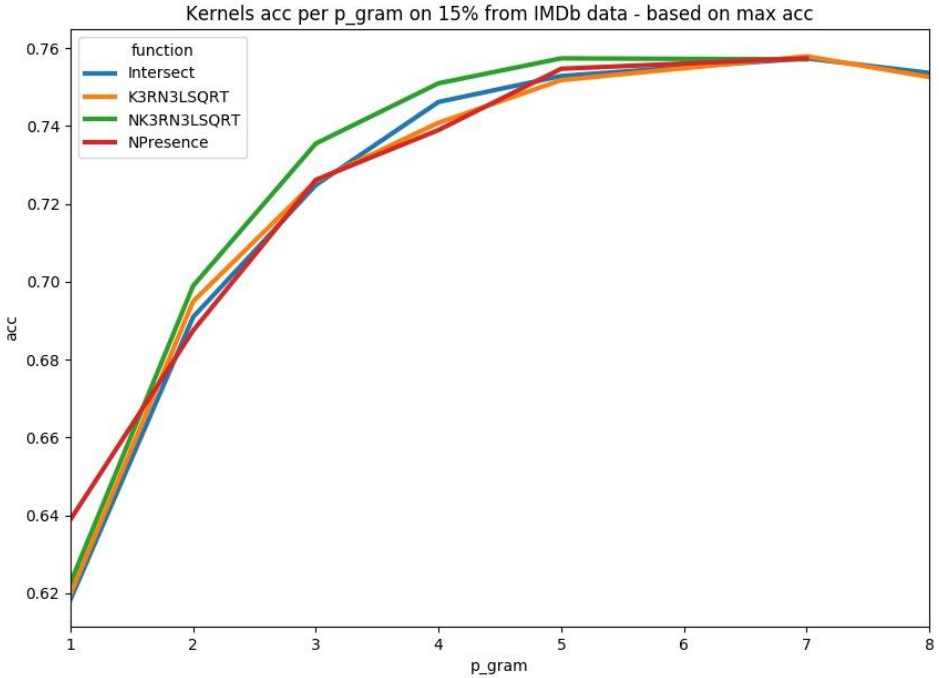

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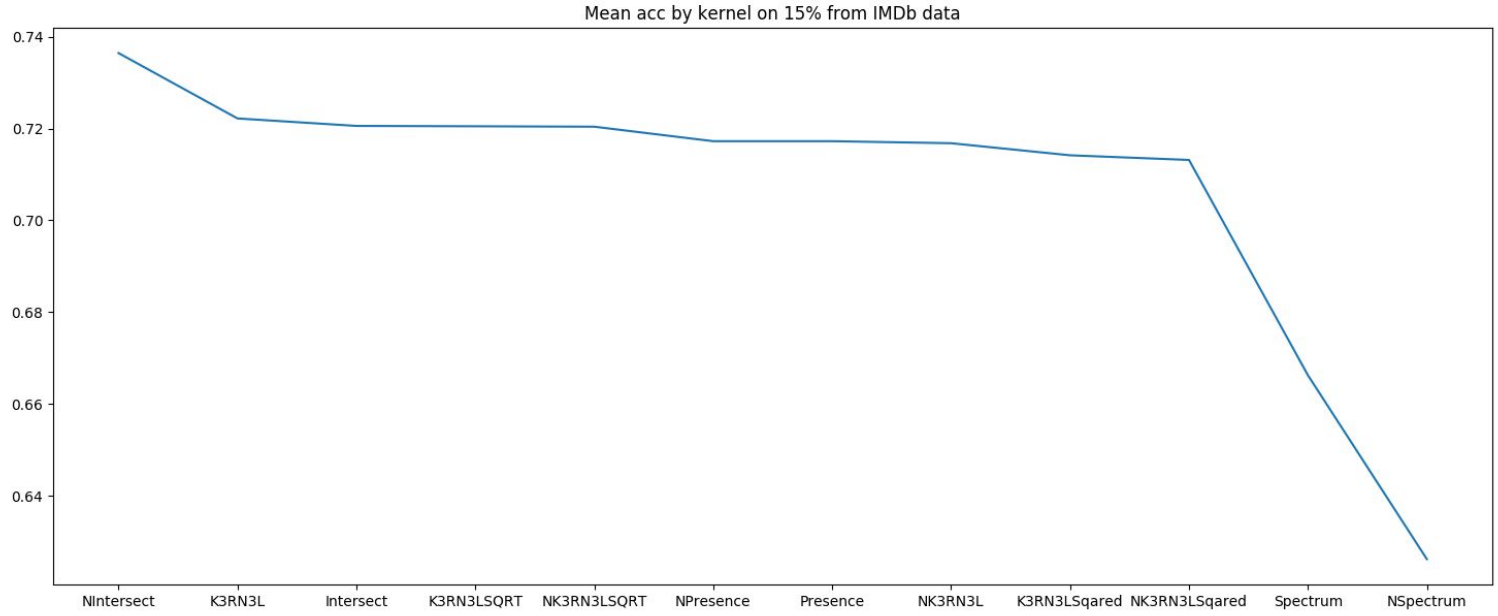

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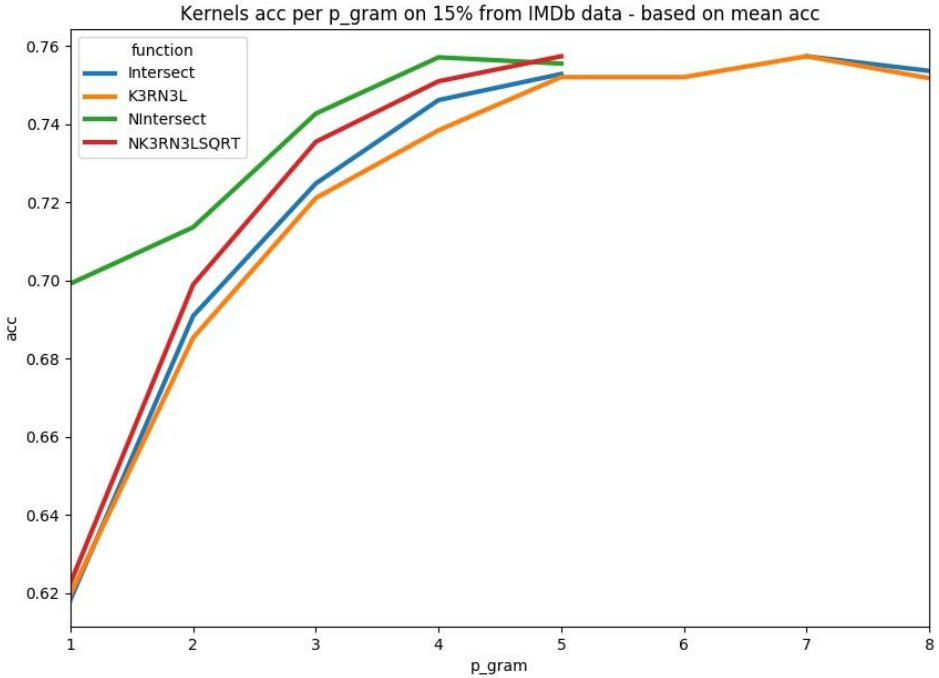

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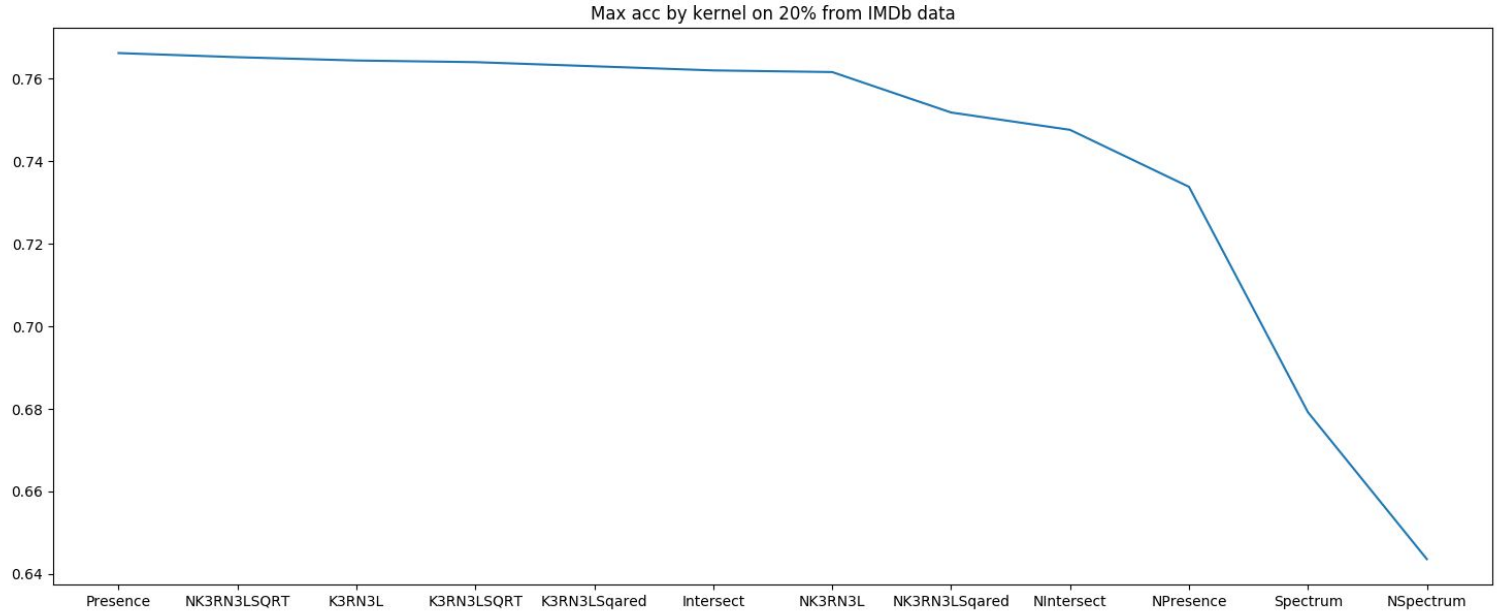

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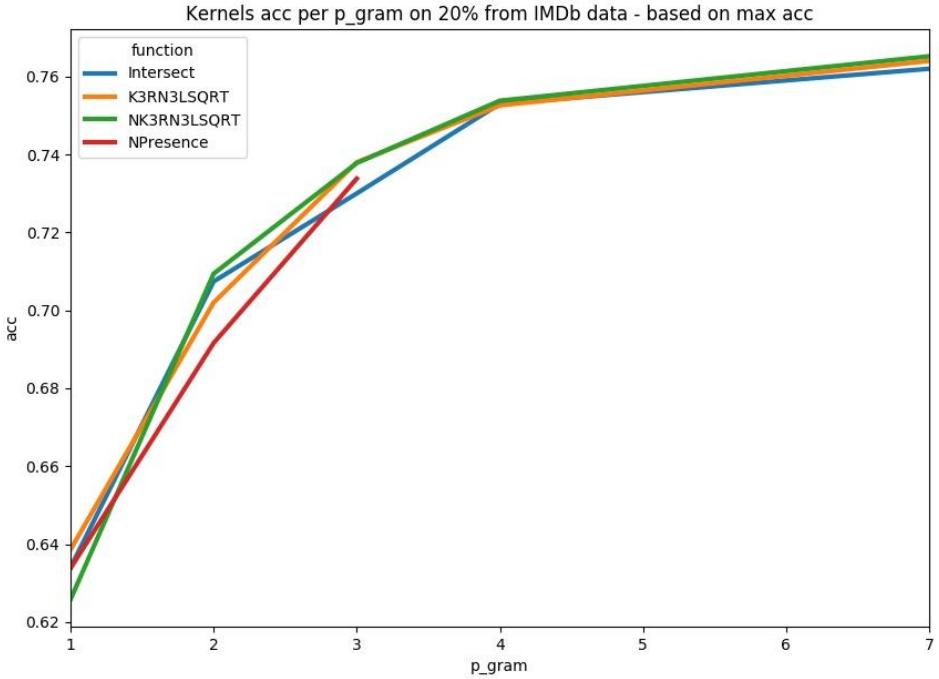

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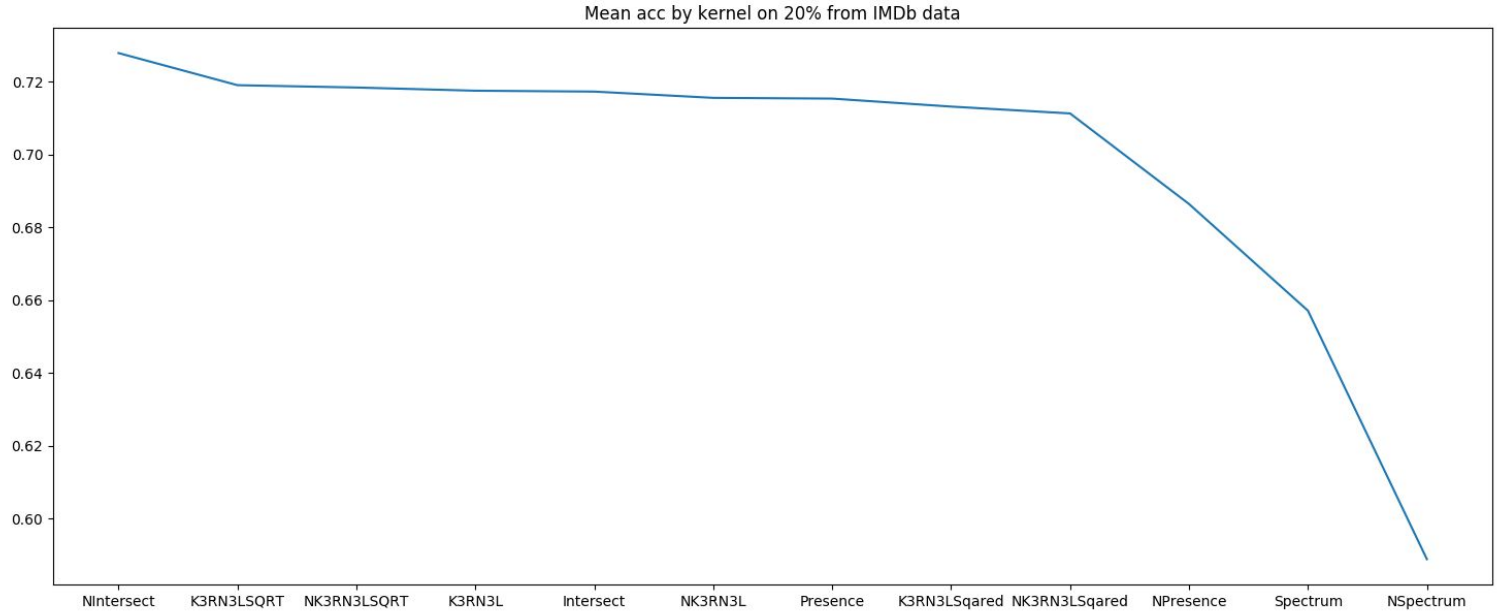

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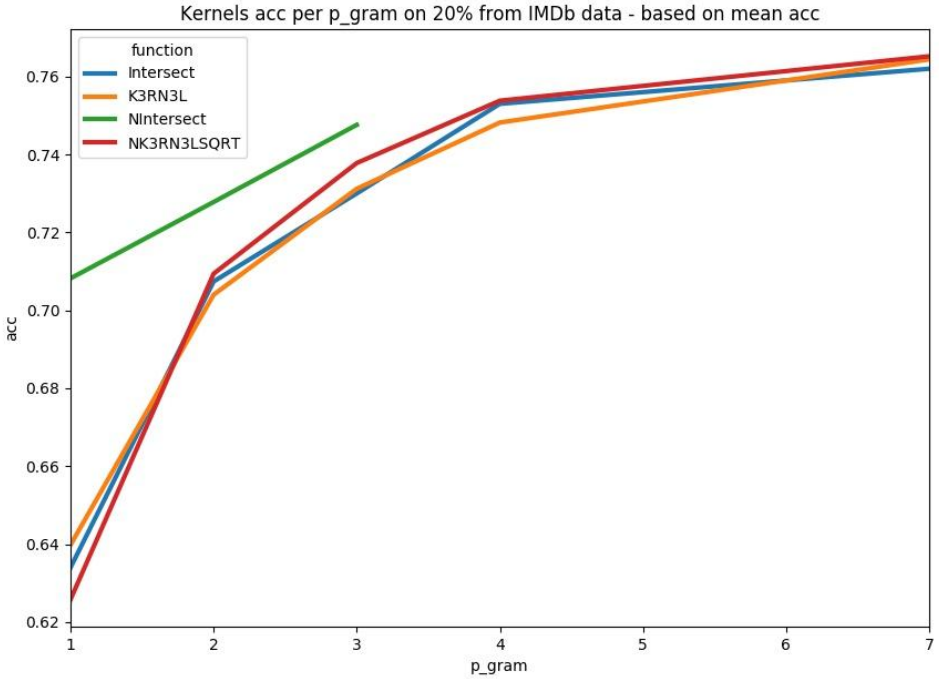
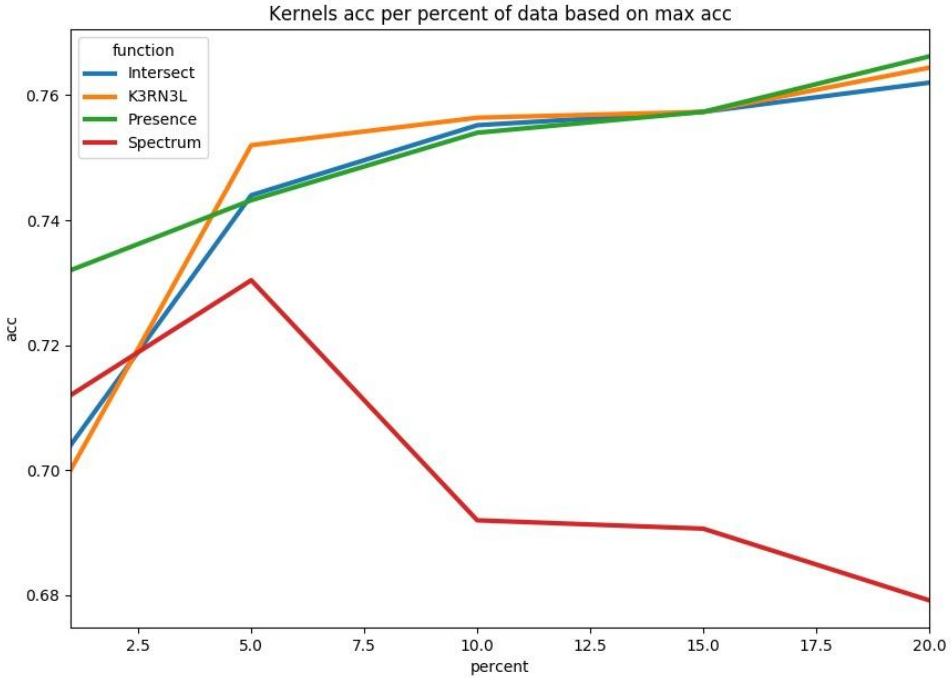


Evolution of acc over % from data



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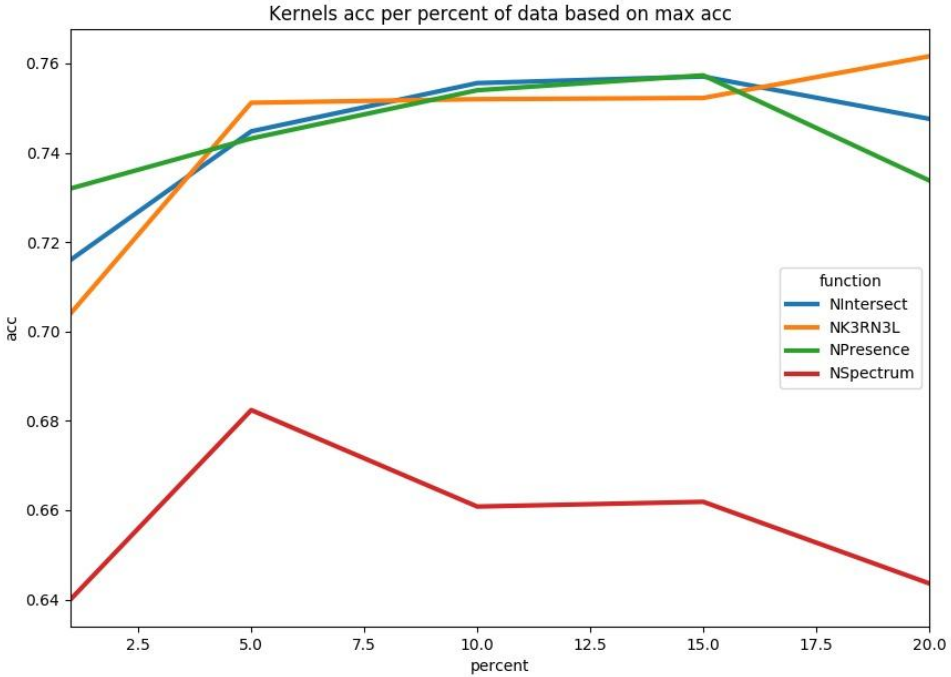

Conlusions

We think that K3RN3L worked much better than intersect in the bots task because the texts were longer and we think that it was aprox. the same on IMDb test because the reviews were significantly shorter.

Our implementation

Our implementation can be found at

https://github.com/teo2mirce/Digi24VsAntena3

https://github.com/adilspas/Bots-Gender-Profiling


Thanks!