Authorship Verification via k-Nearest Neighbor Estimation

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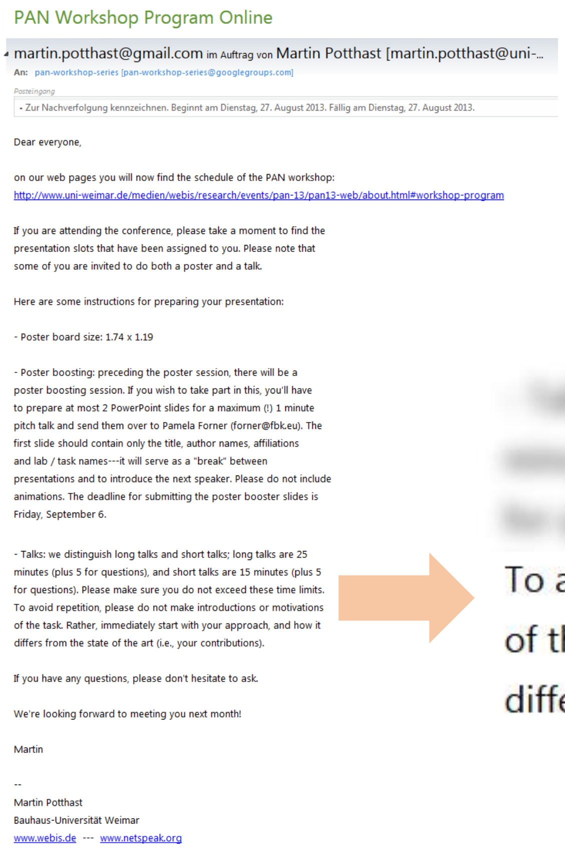
OUTLINE

- Verification schemes
- Features & Feature-Categories
- Our approach
- Evaluation
- Benefits / challenges / future work

MOTIVATION



PAN Workshop Program Online

martin.potthast@gmail.com im Auftrag von Martin Potthast [martin.potthast@uni-...

An: pan-workshop-series [pan-workshop-series@googlegroups.com]

Posteingang

- Zur Nachverfolgung kennzeichnen. Beginnt am Dienstag, 27. August 2013. Fällig am Dienstag, 27. August 2013.

Dear everyone,

on our web pages you will now find the schedule of the PAN workshop:
http://www.uni-weimar.de/medien/webis/research/events/pan-13/pan13-web/about.html#workshop-program

If you are attending the conference, please take a moment to find the presentation slots that have been assigned to you. Please note that some of you are invited to do both a poster and a talk.

Here are some instructions for preparing your presentation:

- Poster board size: 1.74 x 1.19

- Poster boosting: preceding the poster session, there will be a poster boosting session. If you wish to take part in this, you'll have to prepare at most 2 PowerPoint slides for a maximum (!) 1 minute pitch talk and send them over to Pamela Forner (forner@fbk.eu). The first slide should contain only the title, author names, affiliations and lab / task names---it will serve as a "break" between presentations and to introduce the next speaker. Please do not include animations. The deadline for submitting the poster booster slides is Friday, September 6.

- Talks: we distinguish long talks and short talks; long talks are 25 minutes (plus 5 for questions), and short talks are 15 minutes (plus 5 for questions). Please make sure you do not exceed these time limits. To avoid repetition, please do not make introductions or motivations of the task. Rather, immediately start with your approach, and how it differs from the state of the art (i.e., your contributions).

If you have any questions, please don't hesitate to ask.

We're looking forward to meeting you next month!

Martin

--
Martin Potthast
Bauhaus-Universität Weimar
www.webis.de --- www.netspeak.org

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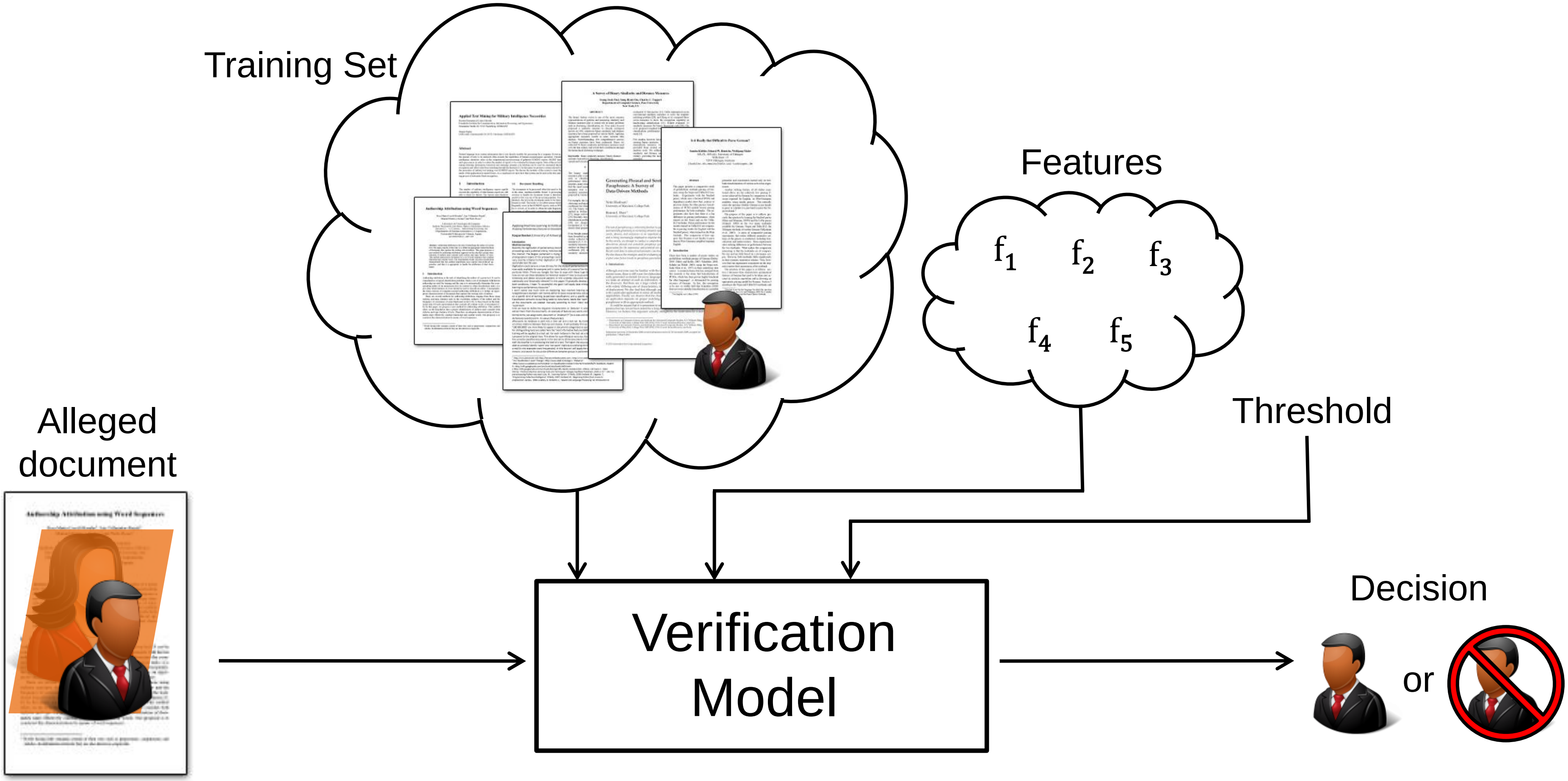
☺ So, let's start immediately…

VERIFICATION SCHEME (CLASSICAL VERSION…)



Training Set

Features

f_1 f_2 f_3 f_4 f_5

Threshold

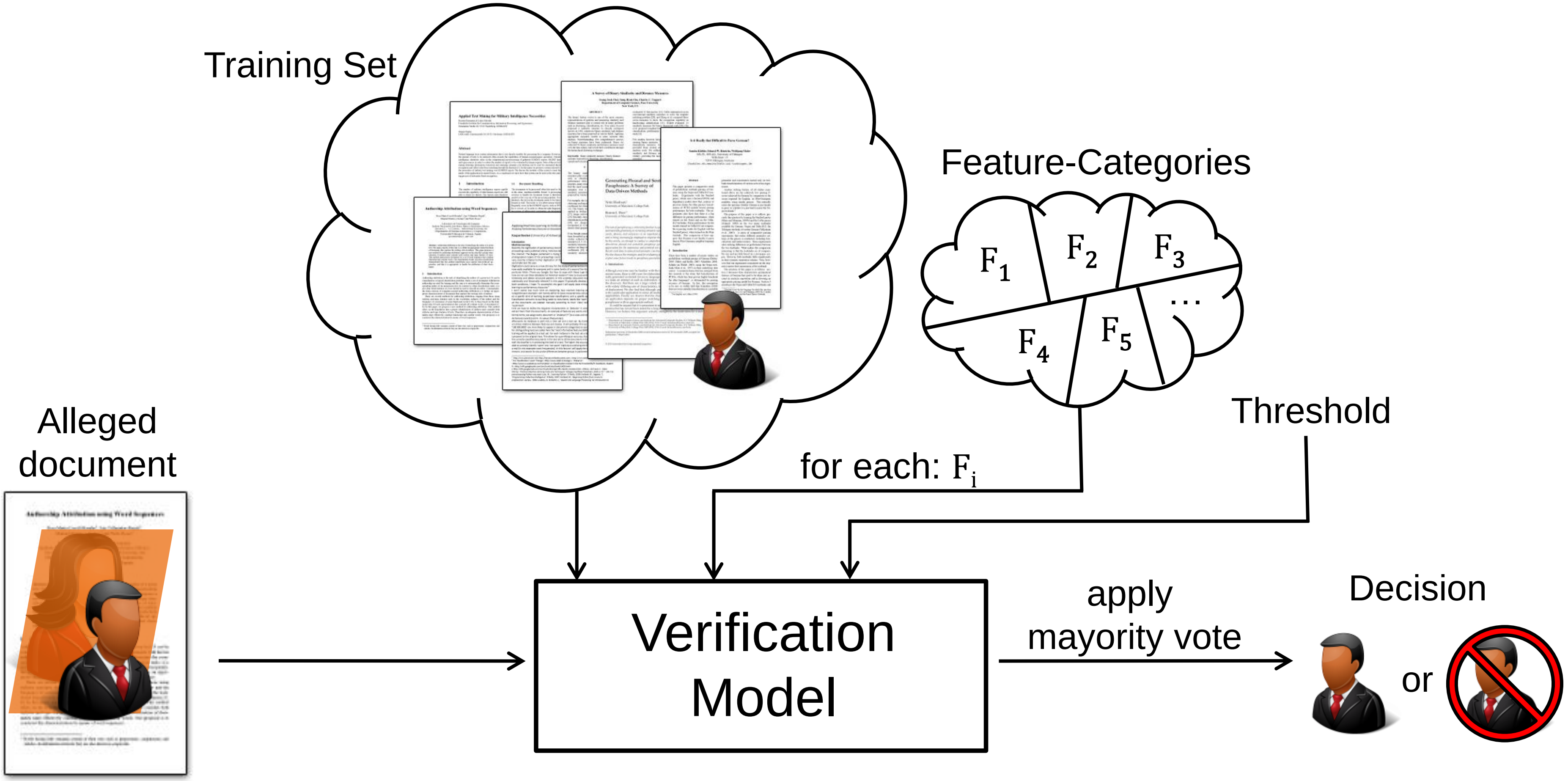
Alleged document

Verification Model

Decision

or

VERIFICATION SCHEME (OUR VERSION…)



Training Set

Feature-Categories

F_1 F_2 F_3 F_4 F_5 …

Alleged document

for each: F_i

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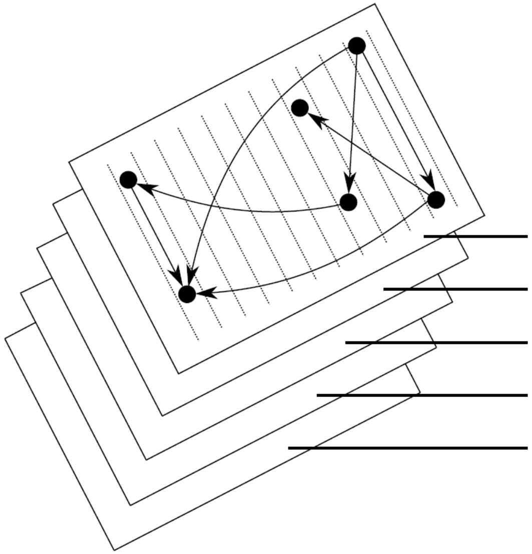

Semantic layer

Syntactic layer

Lexical layer

Character layer

Phoneme layer

There are even more, e.g. Layout layer

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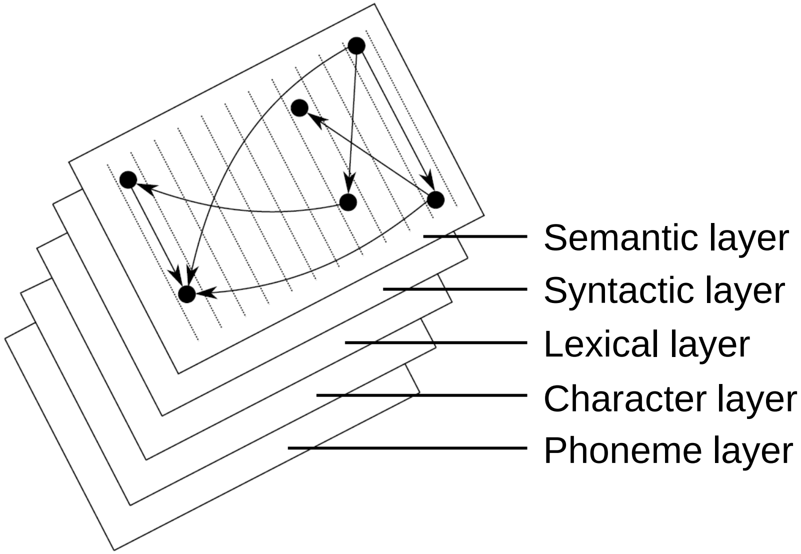

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- Instead of "layers" we prefer to use the term "Feature-Categories"…

FEATURE CATEGORIES

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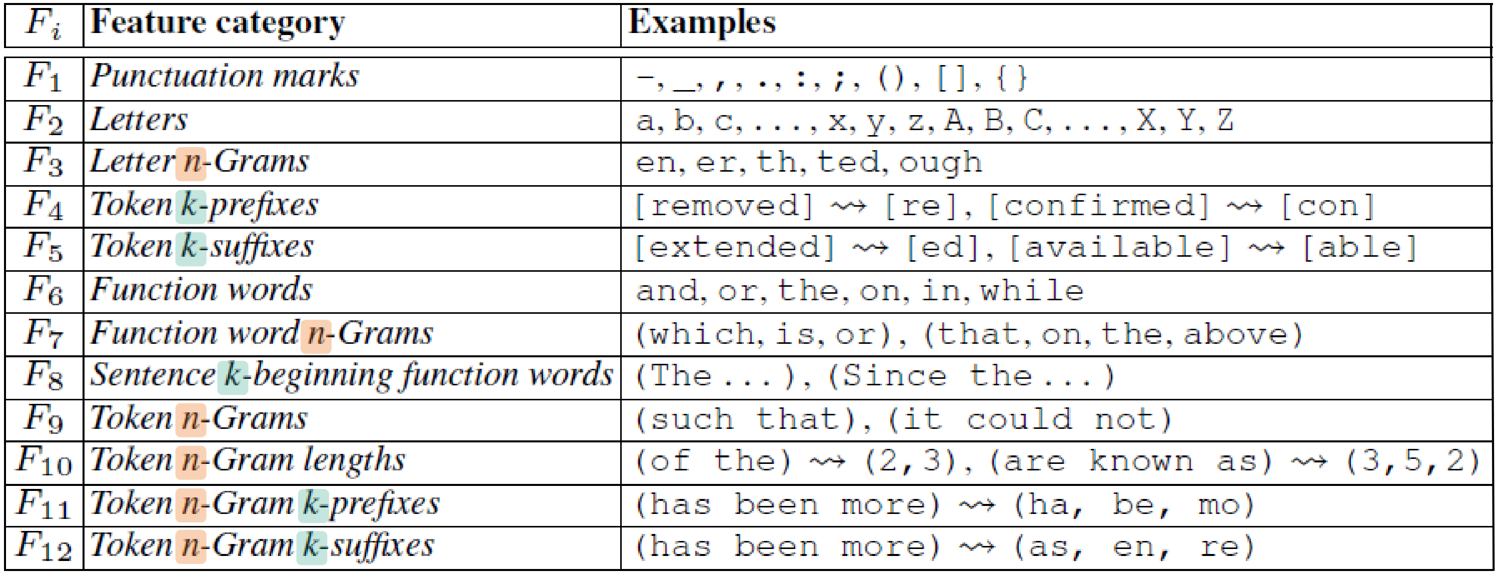

F_i	**Feature category**	**Examples**
F_1	*Punctuation marks*	-, _, ,, ., :, ;, (), [], {}
F_2	*Letters*	a, b, c, . . . , x, y, z, A, B, C, . . . , X, Y, Z
F_3	*Letter n-Grams*	en, er, th, ted, ough
F_4	*Token k-prefixes*	[removed] ⇝ [re], [confirmed] ⇝ [con]
F_5	*Token k-suffixes*	[extended] ⇝ [ed], [available] ⇝ [able]
F_6	*Function words*	and, or, the, on, in, while
F_7	*Function word n-Grams*	(which, is, or), (that, on, the, above)
F_8	*Sentence k-beginning function words*	(The . . .), (Since the . . .)
F_9	*Token n-Grams*	(such that), (it could not)
F_{10}	*Token n-Gram lengths*	(of the) ⇝ (2,3), (are known as) ⇝ (3,5,2)
F_{11}	*Token n-Gram k-prefixes*	(has been more) ⇝ (ha, be, mo)
F_{12}	*Token n-Gram k-suffixes*	(has been more) ⇝ (as, en, re)

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- **(Unsatisfactory) solution:** random examination…

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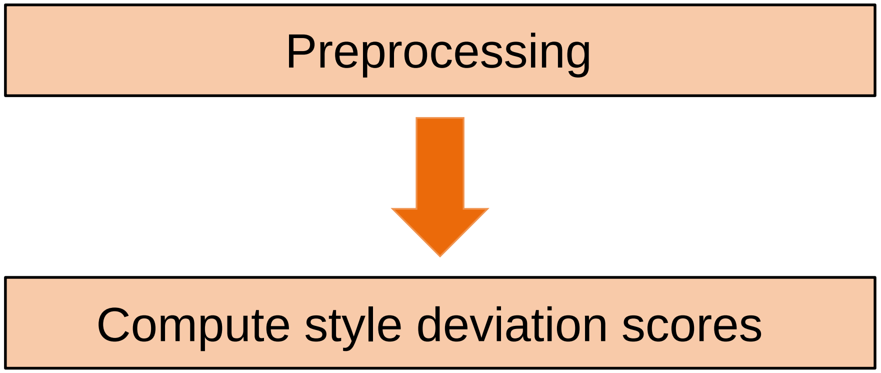

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Compute style deviation scores

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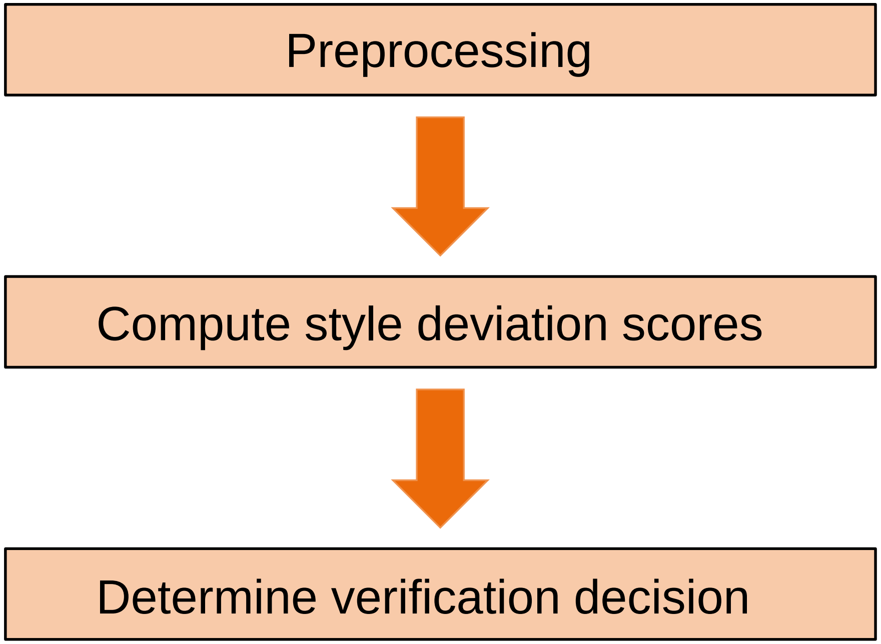
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Important to increase quality of extracted features!

→ e.g. removing citations, markup-tags, formulas, non-words, etc.

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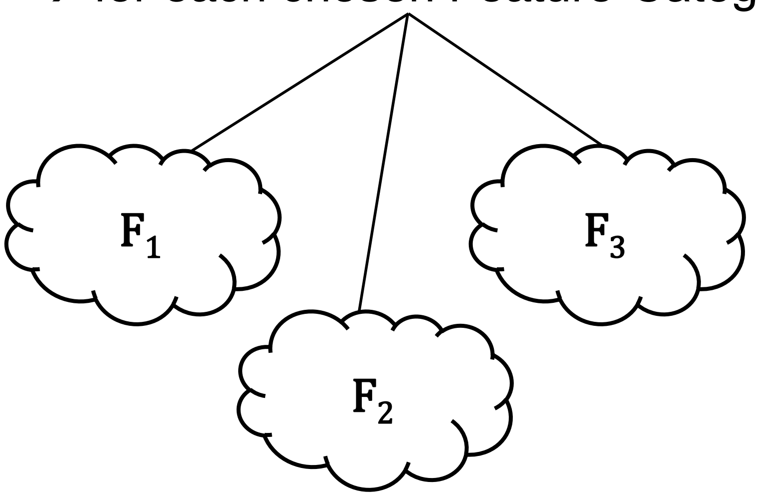

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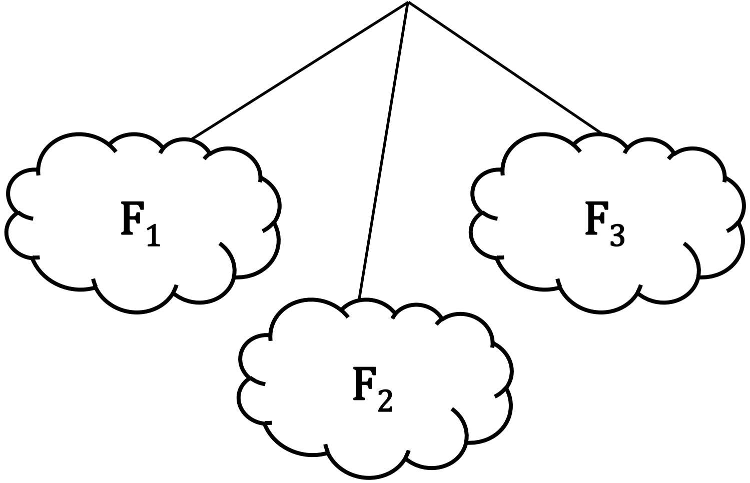

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- **Important:** Majority-voting needs an uneven number of individual decisions
  → hence, number of $\mathbf{F}_i$ is always odd

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CASED

Fraunhofer SIT

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In most of the cases: ***1*** *performs very well…*

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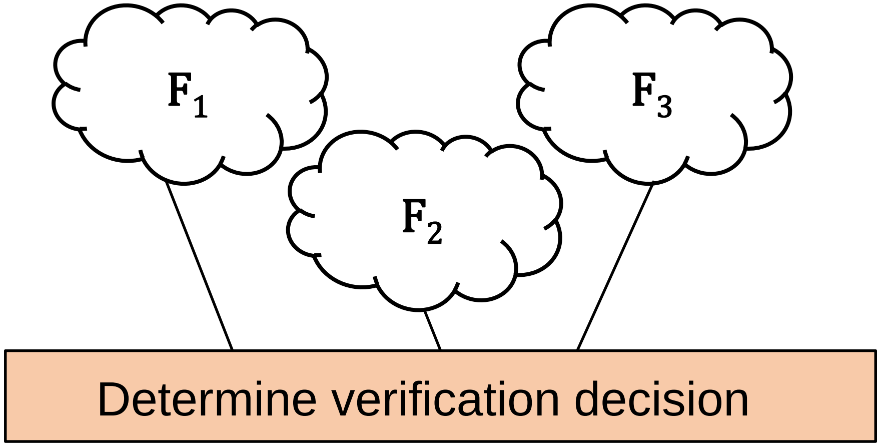

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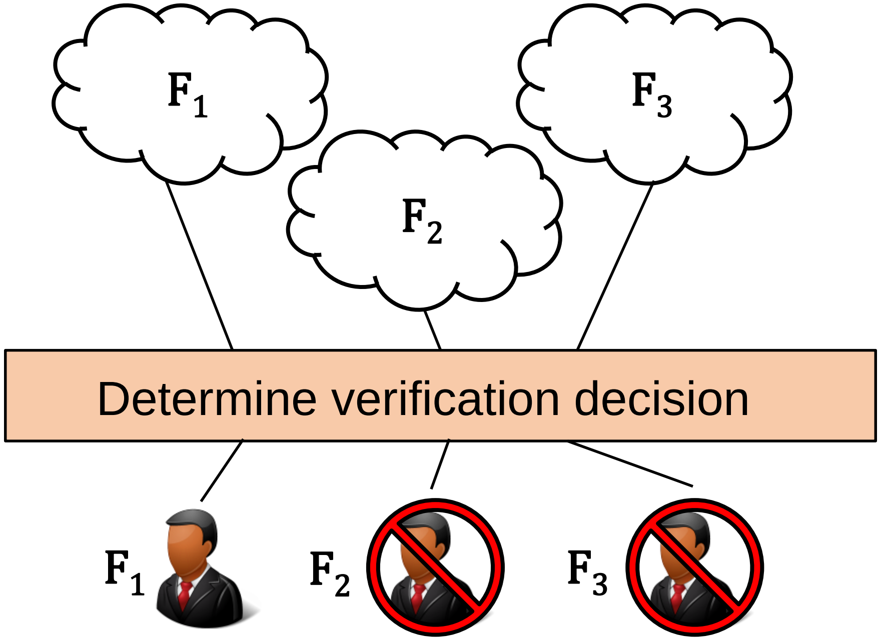

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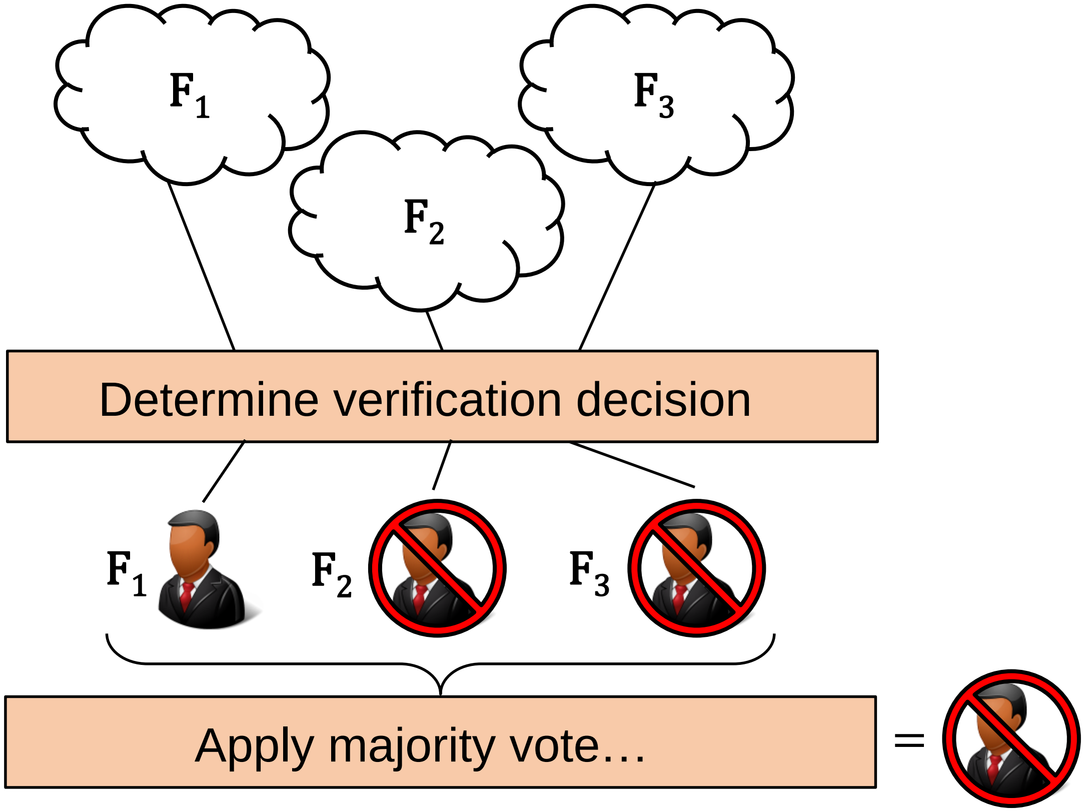

Determine verification decision

Apply majority vote…

EVALUATION: USED MEASURES

Simple accuracy:

$$\varnothing = \frac{\varnothing_{\mathcal{C}_{GR}} + \varnothing_{\mathcal{C}_{EN}} + \ldots}{|\mathcal{C}_{GR} \cup \mathcal{C}_{EN} \cup \ldots|} \text{ , with } \varnothing_{\mathcal{C}_i} = \frac{\text{Number of correct answers per dataset } \mathcal{C}_i}{\text{Total number of documents per dataset } \mathcal{C}_i}$$

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Weighted accuracy:

$$(\text{weighted})\varnothing = \frac{|\mathcal{C}_{GR}| \cdot \varnothing_{\mathcal{C}_{GR}} + |\mathcal{C}_{EN}| \cdot \varnothing_{\mathcal{C}_{EN}} + \ldots}{|\mathcal{C}_{GR} \cup \mathcal{C}_{EN} \cup \ldots|}$$

EVALUATION: TRAIN SET (PAN ONLY)

- Evaluation results according to "PAN13-AI-Training Corpus"

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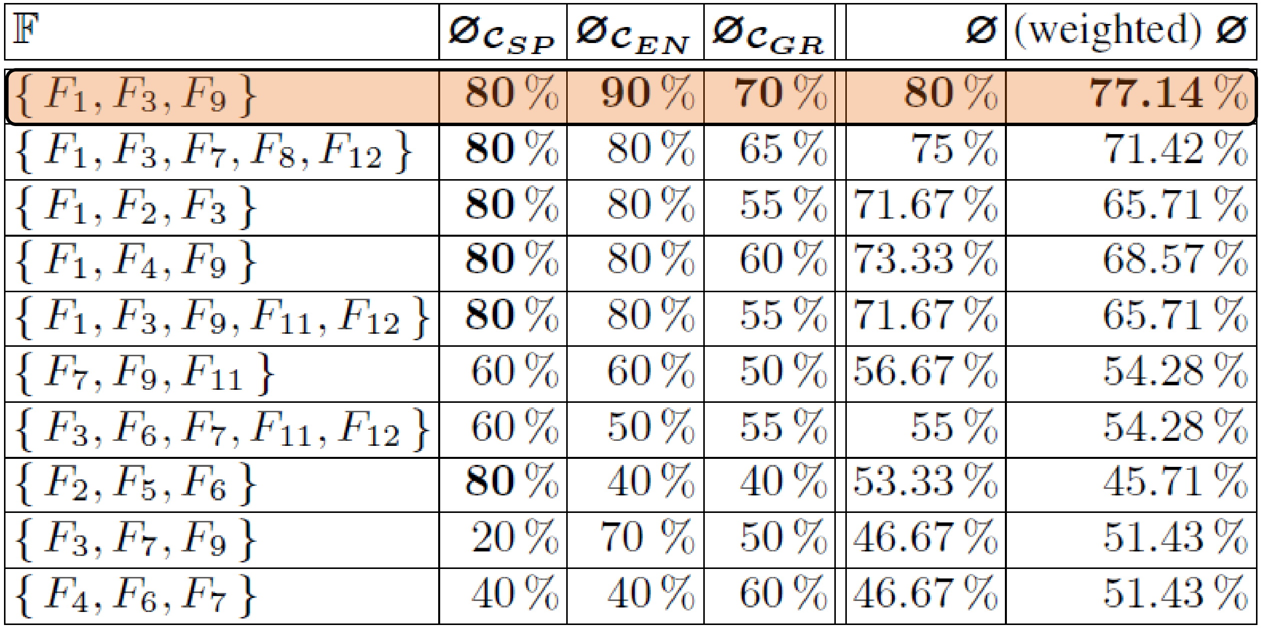

$\mathbb{F}$	$\varnothing c_{SP}$	$\varnothing c_{EN}$	$\varnothing c_{GR}$	$\varnothing$	(weighted) $\varnothing$
$\{ F_1, F_3, F_9 \}$	**80 %**	**90 %**	**70 %**	**80 %**	**77.14 %**
$\{ F_1, F_3, F_7, F_8, F_{12} \}$	**80 %**	80 %	65 %	75 %	71.42 %
$\{ F_1, F_2, F_3 \}$	**80 %**	80 %	55 %	71.67 %	65.71 %
$\{ F_1, F_4, F_9 \}$	**80 %**	80 %	60 %	73.33 %	68.57 %
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$\{ F_7, F_9, F_{11} \}$	60 %	60 %	50 %	56.67 %	54.28 %
$\{ F_3, F_6, F_7, F_{11}, F_{12} \}$	60 %	50 %	55 %	55 %	54.28 %
$\{ F_2, F_5, F_6 \}$	**80 %**	40 %	40 %	53.33 %	45.71 %
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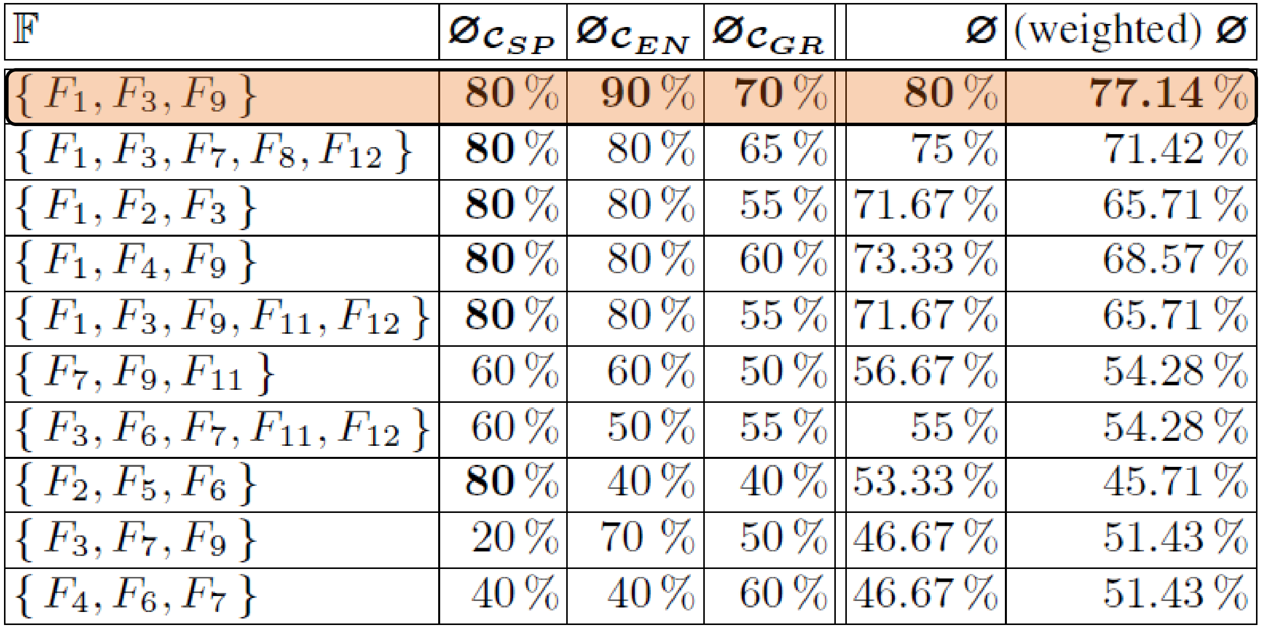

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- **Note:** the first one is the **best** $\mathbf{F}_\mathrm{i}$ - combination out of **2^{12}** = **4096**

EVALUATION: TRAIN SET (PAN + GERMAN CORPUS)

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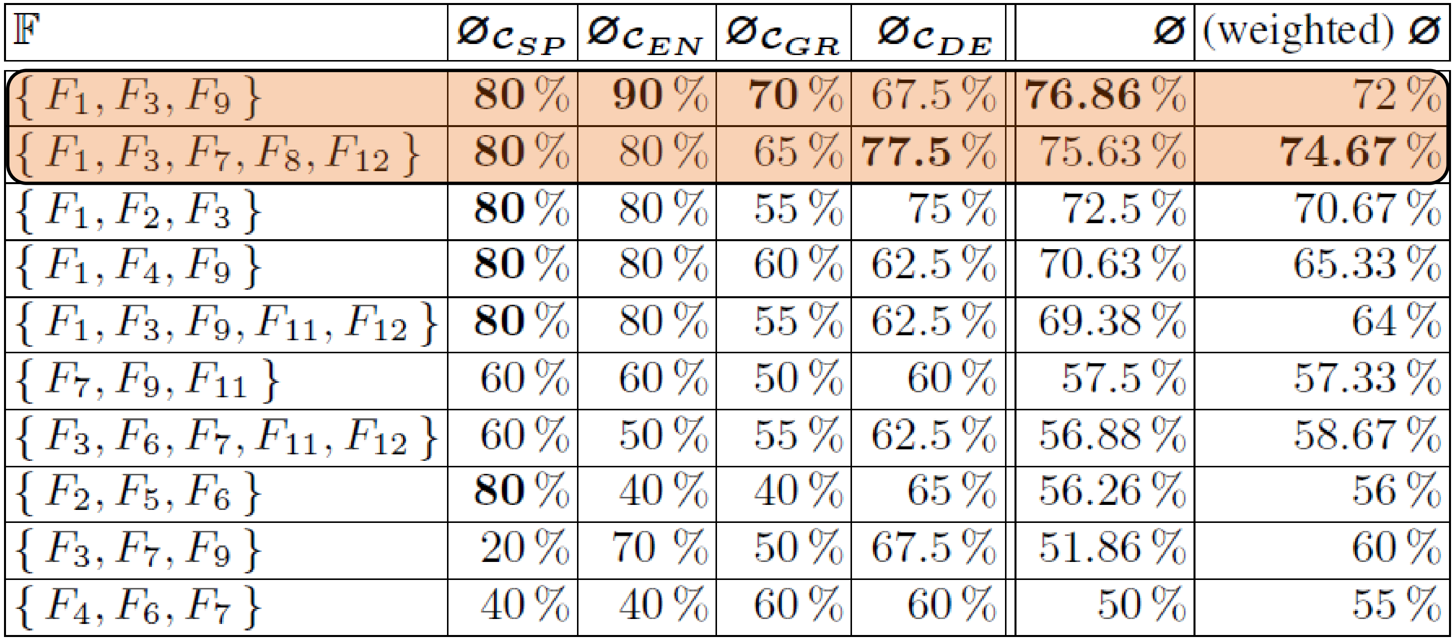

$\mathbb{F}$	$\varnothing c_{SP}$	$\varnothing c_{EN}$	$\varnothing c_{GR}$	$\varnothing c_{DE}$	$\varnothing$	(weighted) $\varnothing$
$\{F_1, F_3, F_9\}$	**80 %**	**90 %**	**70 %**	67.5 %	**76.86 %**	72 %
$\{F_1, F_3, F_7, F_8, F_{12}\}$	**80 %**	80 %	65 %	**77.5 %**	75.63 %	**74.67 %**
$\{F_1, F_2, F_3\}$	**80 %**	80 %	55 %	75 %	72.5 %	70.67 %
$\{F_1, F_4, F_9\}$	**80 %**	80 %	60 %	62.5 %	70.63 %	65.33 %
$\{F_1, F_3, F_9, F_{11}, F_{12}\}$	**80 %**	80 %	55 %	62.5 %	69.38 %	64 %
$\{F_7, F_9, F_{11}\}$	60 %	60 %	50 %	60 %	57.5 %	57.33 %
$\{F_3, F_6, F_7, F_{11}, F_{12}\}$	60 %	50 %	55 %	62.5 %	56.88 %	58.67 %
$\{F_2, F_5, F_6\}$	**80 %**	40 %	40 %	65 %	56.26 %	56 %
$\{F_3, F_7, F_9\}$	20 %	70 %	50 %	67.5 %	51.86 %	60 %
$\{F_4, F_6, F_7\}$	40 %	40 %	60 %	60 %	50 %	55 %

EVALUATION: TRAIN SET (PAN → INFLUENCE OF PARAMETERS)

- Evaluation results according to "PAN13-AI-Training Corpus" with the best combination $\{F_1, F_3, F_9\}$ nd various parameter-settings

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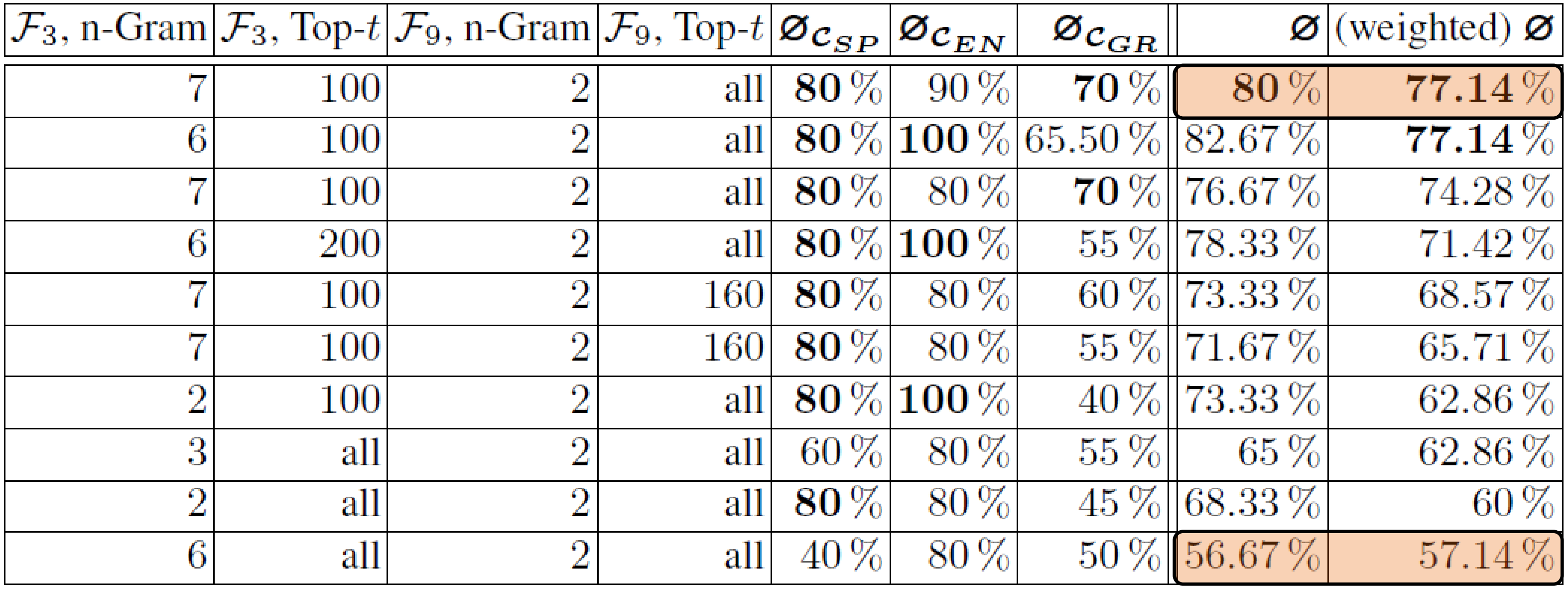
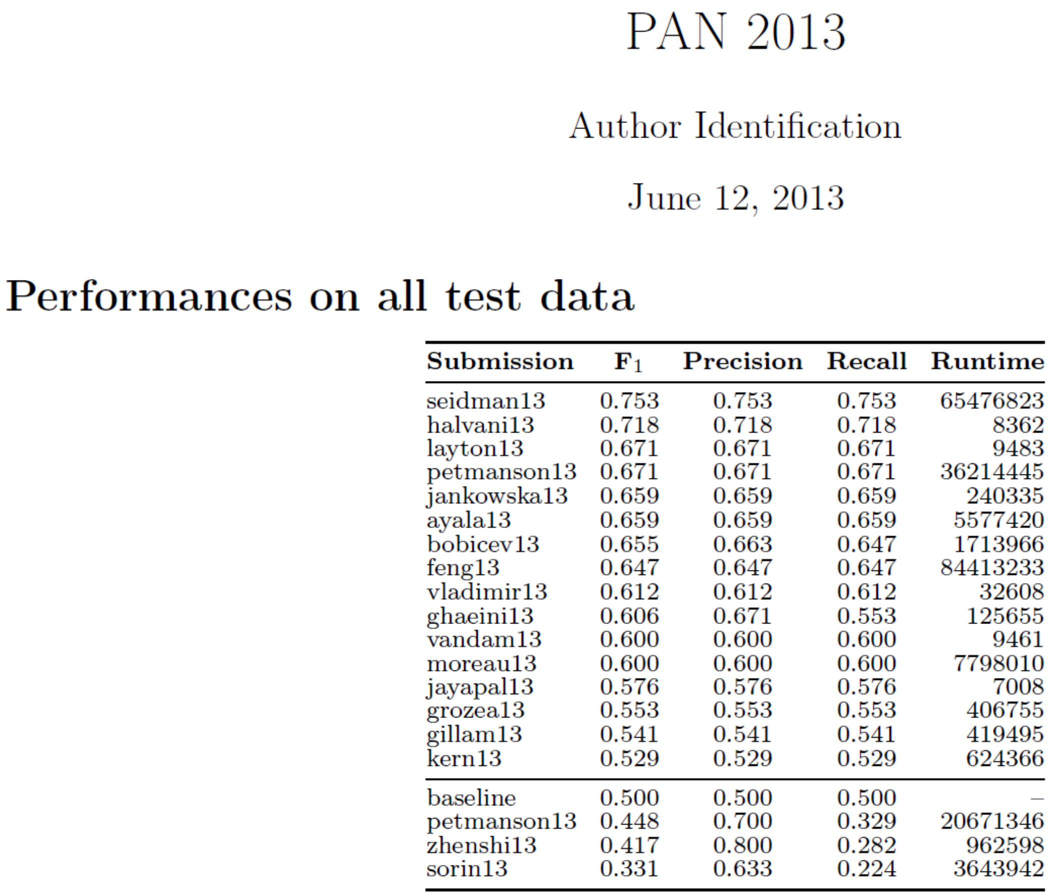


$\mathcal{F}_3$, n-Gram	$\mathcal{F}_3$, Top-t	$\mathcal{F}_9$, n-Gram	$\mathcal{F}_9$, Top-t	$\varnothing c_{SP}$	$\varnothing c_{EN}$	$\varnothing c_{GR}$	$\varnothing$	(weighted) $\varnothing$
7	100	2	all	**80** %	90 %	**70** %	**80** %	**77.14** %
6	100	2	all	**80** %	**100** %	65.50 %	82.67 %	**77.14** %
7	100	2	all	**80** %	80 %	**70** %	76.67 %	74.28 %
6	200	2	all	**80** %	**100** %	55 %	78.33 %	71.42 %
7	100	2	160	**80** %	80 %	60 %	73.33 %	68.57 %
7	100	2	160	**80** %	80 %	55 %	71.67 %	65.71 %
2	100	2	all	**80** %	**100** %	40 %	73.33 %	62.86 %
3	all	2	all	60 %	80 %	55 %	65 %	62.86 %
2	all	2	all	**80** %	80 %	45 %	68.33 %	60 %
6	all	2	all	40 %	80 %	50 %	56.67 %	57.14 %

EVALUATION: TEST SET



PAN 2013

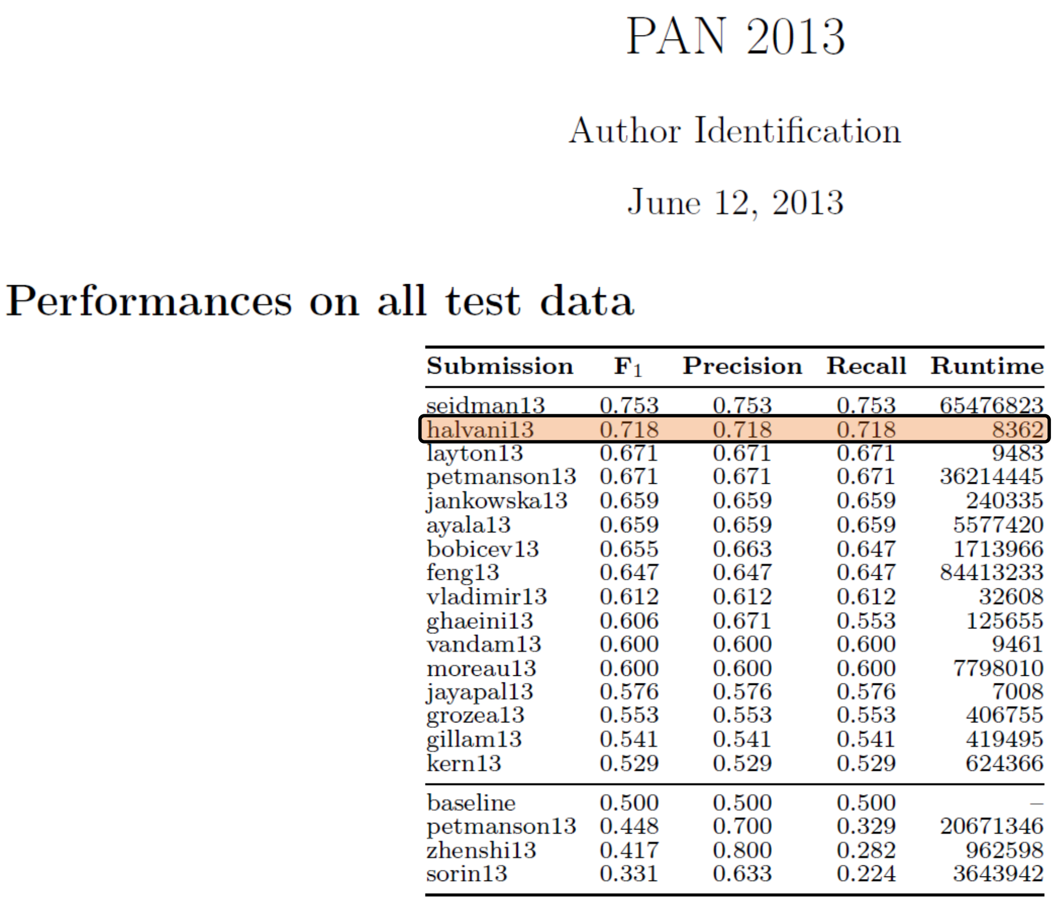
Author Identification

June 12, 2013

Performances on all test data

Submission	F_1	Precision	Recall	Runtime
seidman13	0.753	0.753	0.753	65476823
halvani13	0.718	0.718	0.718	8362
layton13	0.671	0.671	0.671	9483
petmanson13	0.671	0.671	0.671	36214445
jankowska13	0.659	0.659	0.659	240335
ayala13	0.659	0.659	0.659	5577420
bobicev13	0.655	0.663	0.647	1713966
feng13	0.647	0.647	0.647	84413233
vladimir13	0.612	0.612	0.612	32608
ghaeini13	0.606	0.671	0.553	125655
vandam13	0.600	0.600	0.600	9461
moreau13	0.600	0.600	0.600	7798010
jayapal13	0.576	0.576	0.576	7008
grozea13	0.553	0.553	0.553	406755
gillam13	0.541	0.541	0.541	419495
kern13	0.529	0.529	0.529	624366
baseline	0.500	0.500	0.500	–
petmanson13	0.448	0.700	0.329	20671346
zhenshi13	0.417	0.800	0.282	962598
sorin13	0.331	0.633	0.224	3643942

EVALUATION: TEST SET



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If runtime would count too… ☺

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Threshold, distance function(s), Feature-Categories (and their parameters),…

CHALLENGES / FUTURE WORK

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  Inscrutability of the methods parameter-space ☹
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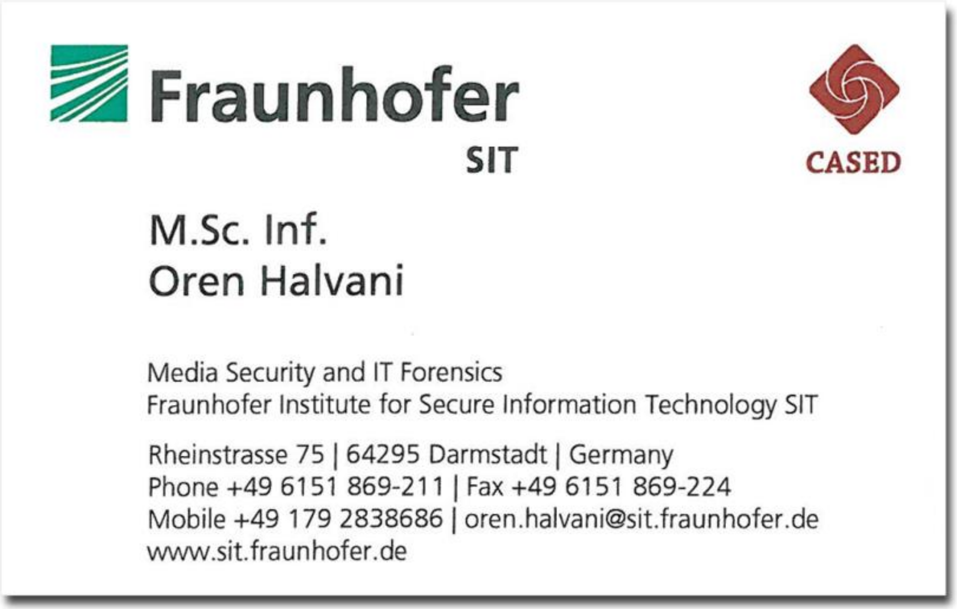
- **Possible Solution:**
  One of our students is currently writing his thesis to answer this question

Thank you very much for your attention!



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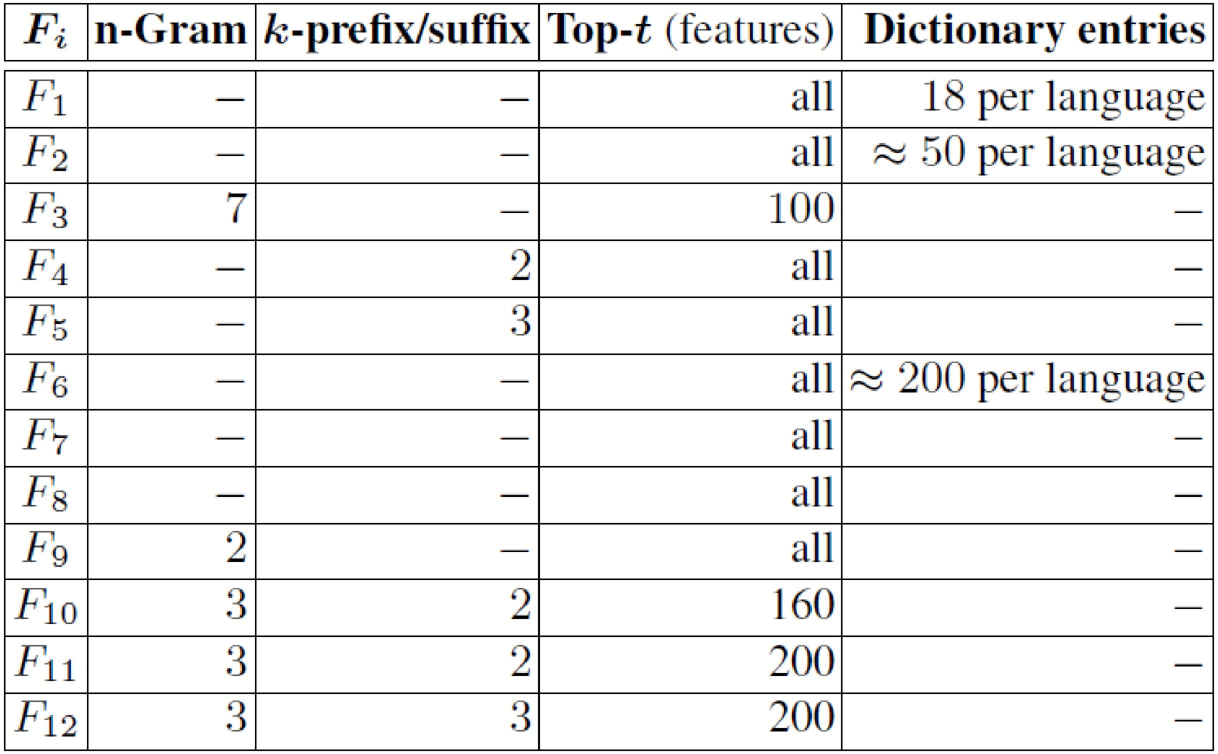
www.sit.fraunhofer.de

USED PARAMETER-SETTINGS

- What kind of parameters were used for PAN and the german corpus…?



F_i	n-Gram	k-prefix/suffix	Top-t (features)	Dictionary entries
F_1	–	–	all	18 per language
F_2	–	–	all	≈ 50 per language
F_3	7	–	100	–
F_4	–	2	all	–
F_5	–	3	all	–
F_6	–	–	all	≈ 200 per language
F_7	–	–	all	–
F_8	–	–	all	–
F_9	2	–	all	–
F_{10}	3	2	160	–
F_{11}	3	2	200	–
F_{12}	3	3	200	–