Overview of the Authorship Verification Task at PAN 2022

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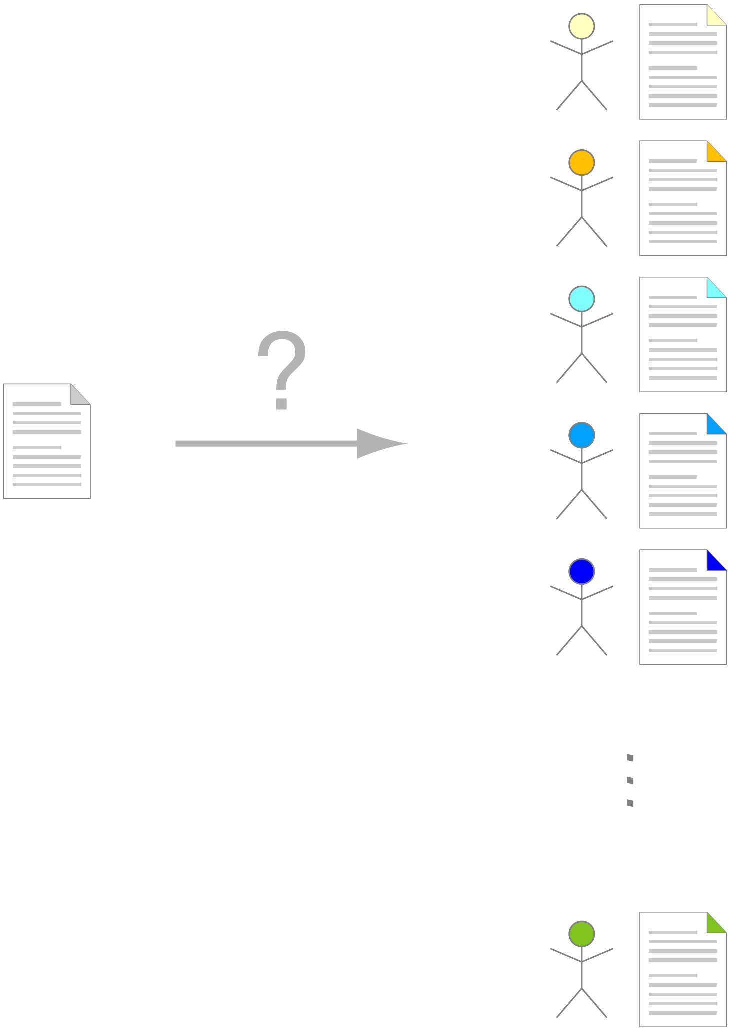
Authorship Verification



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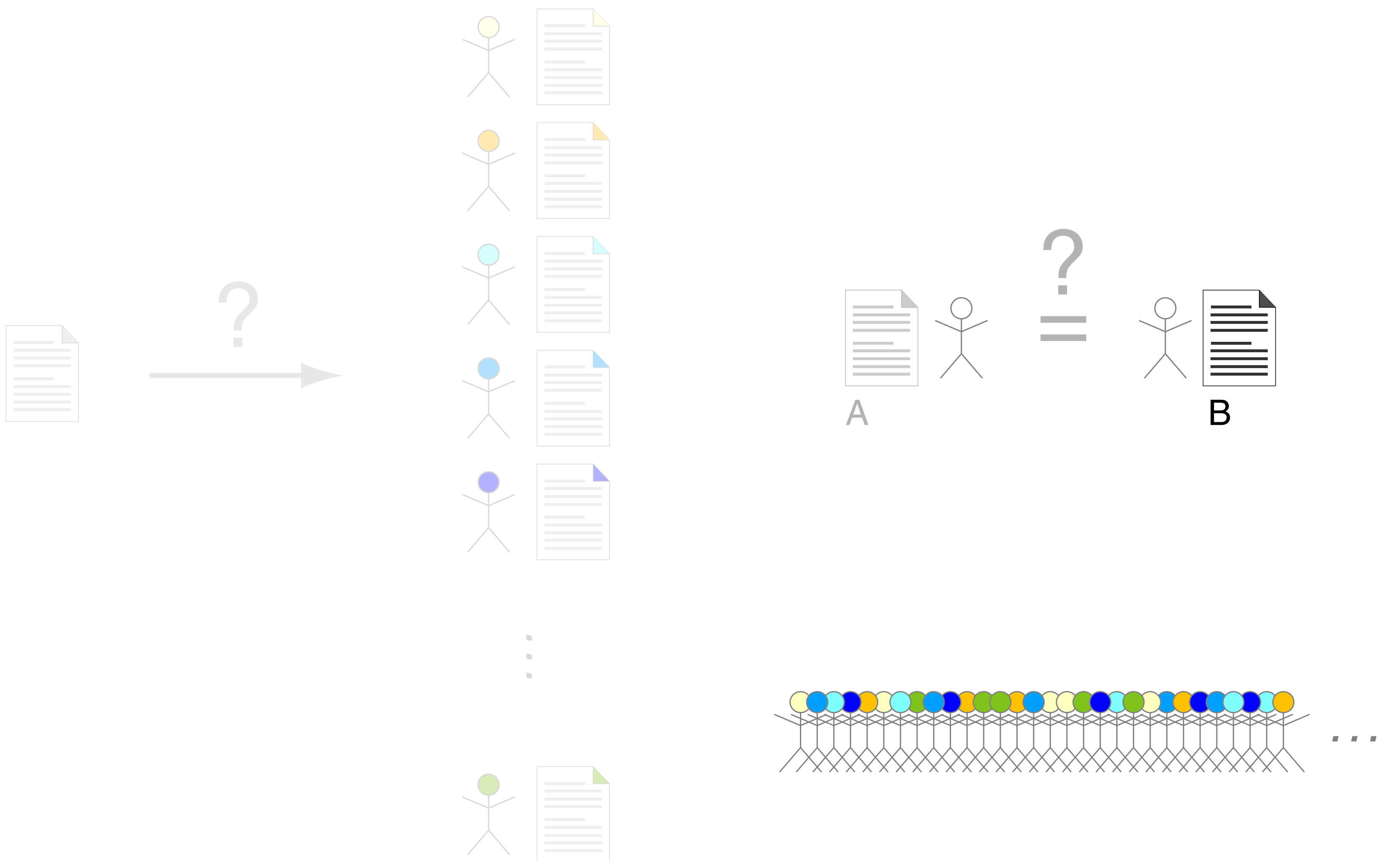

PAN 2020–2022 Overview

1. PAN 2020:
   Closed-set verification on fanfiction texts

2. PAN 2021:
   Open-set verification on fanfiction texts

3. PAN 2022:
   “Surprise task”: cross-discourse type authorship verification

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   “Surprise task”: cross-discourse type authorship verification

The Data

The task's training and test data is based on the *Aston 100 Idiolects*[1] corpus:

- Text samples by 112 individuals using various discourse types.
- Authors have similar age characteristics.
- Authors are native speakers of English.
- Topic is unrestricted.

[1] Kredens, Heini, and Pezik; 2021

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Selected Discourse Types:

Essays, emails, business memos, text messages.

[1] Kredens, Heini, and Pezik; 2021

The Data (continued)

Subset	Training	Test
Author match	*Text pairs*	
Positive (same author)	6,132 (50.0%)	5,239 (50.0%)
Negative (different author)	6,132 (50.0%)	5,239 (50.0%)
Discourse type pairings	*Text pairs*	
Email–Text message	7,484 (61.0%)	6,092 (58.1%)
Essay–Email	1,618 (13.2%)	1,454 (13.9%)
Essay–Text message	1,182 (9.6%)	1,128 (10.8%)
Business memo–Email	1,014 (8.3%)	900 (8.6%)
Business memo–Text message	780 (6.4%)	718 (6.9%)
Essay–Business memo	186 (1.5%)	186 (1.8%)
Discourse type	*Text length (avg. chars)*	
Essay	11,098	10,117
Email	2,385	2,323
Business memo	1,255	1,042
Text message	611	601

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The Data (continued)

Source Data:

`pairs.jsonl:`


```
{"id": "a09fdc6b-ed15-48c5-9d2e-572f989b9b45",
     "discourse_type": ["essay", "text_message"],
     "pair": ["Text 1...", "Text 2..."]}
...
```


`truth.jsonl:`


```
{"id": "a09fdc6b-ed15-48c5-9d2e-572f989b9b45",
     "same": false, "authors": ["en_110", "en_112"]}
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The Data (continued)

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Answer Submission:


```
{"id": "a09fdc6b-ed15-48c5-9d2e-572f989b9b45", "value": 0.4921}
...
```

Evaluation

Answers are in the range $[0, 1]$ indicating the *same author* class probability:

- > 0.5: most likely same author
- < 0.5: most likely different authors
- $= 0.5$: no answer commitment

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Performance is assessed by five measures:

- AUROC: area under the ROC curve
- F_1: Harmonic mean of precision and recall for *same author* class
- $F_{0.5u}$: Precision-weighted F score which rewards non-answers
- C@1: Modified binary accuracy which rewards non-answers
- BRIER: Brier score complement (inverse binary quadratic loss)

Final score is calculated as the arithmetic mean of all five.

Baselines

- CNGDIST22: Distance-based character n-gram model: cosine similarity on most frequent 4-grams with two thresholds for classes or “undecided”.
- COMPRESSOR22: Compression-based model: logistic regression classifier trained on the PPM cross-entropy between texts, scores ≈ 0.5 are set to 0.5.

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Baseline Name	AUROC	C@1	F_1	$F_{0.5u}$	BRIER	MEAN
BASELINE-CNGDIST22	**0.546**	**0.496**	**0.669**	**0.542**	0.749	**0.600**
BASELINE-COMPRESSOR22	0.541	0.493	0.570	0.478	**0.750**	0.566

Submitted Systems

Seven participants handed in their models.

Models were evaluated (but not trained) on the Tira[1] platform.

[1] `https://www.tira.io`

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System	Representation	Architecture	Augm.
NAJAFI22	T5, word unigrams, POS,	CNN	No
	NEs, Punctuation		No
GALICIA22	graph-based, POS	Siamese network	Yes
JINLI22	MPNET		No
LEI22	BERT		No
YIHUIYE22	BERT	TextCNN	Yes
HUANG22	BERT		No
CRESPOSANCHEZ22	word unigrams, doc2vec		Yes
	(text and POS), SOM		Yes

[1] https://www.tira.io

Participant Results

System	AUROC	c@1	F_1	$F_{0.5u}$	BRIER	MEAN
BASELINE-CNGDIST22	0.546	0.496	0.669	0.542	0.749	**0.600**
NAJAFI22	**0.598**	**0.571**	0.576	**0.571**	0.618	0.587
GALICIA22	0.512	0.499	0.628	0.544	0.741	0.585
JINLI22	0.577	0.557	0.581	0.563	0.589	0.573
BASELINE-COMPRESSOR22	0.541	0.493	0.570	0.478	**0.750**	0.566
LEI22	0.539	0.539	0.399	0.488	0.539	0.501
YIHUIYE22	0.542	0.526	0.398	0.461	0.565	0.499
HUANG22	0.519	0.519	0.196	0.328	0.519	0.416
CRESPOSANCHEZ22	0.500	0.500	0	0	0.748	0.350

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Model Biases

System	Positive	Negative	Unanswered
NAJAFI22	5,355	5,083	40
GALICIA22	8,874	1,604	0
JINLI22	5,820	4,658	0
LEI22	2,805	7,673	0
YIHUIYE22	2,841	7,116	521
HUANG22	1,031	9,447	0
CRESPOSANCHEZ22	0	10,478	0

Baseline Name	Positive	Negative	Unanswered
BASELINE-CNGDIST22	9,199	17	1,262
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Explanations?

- Models too complex for the data?
- Data lends itself to overfitting?
- Issues with the test split?
- Task too difficult?
- . . .

Lots of hypotheses to investigate.

Do Previous Systems Perform Better?

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Do Previous Systems Perform Better?

Short answer: No.

First place of last year trails behind last place of this year.

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EMBARCADERORUIZ21	0.538	0.502	0.063	0.116	0.581	0.360
CRESPOSANCHEZ22	0.500	0.500	0	0	0.748	0.350
BOENNINGHOFF21*	0.513	0.501	0.002	0.005	0.531	0.310
WEERASINGHE21	0.488	0.500	0.011	0.027	0.506	0.306

* Previous winner

Conclusion

- Authorship verification is *not* a solved task.
- Bigger models do not necessarily lead to better results.
- Cross-discourse-type verification may be particularly challenging.
- Systems are still failing to find a generalization of “style”.
- Previously successful systems to not transfer well to new task variants.

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Thanks