Deep Bayes Factor Scoring for Authorship Verification

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- **PAN 2022:** Role of judges at court

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Text preprocessing strategies: **Preparing train/dev sets**

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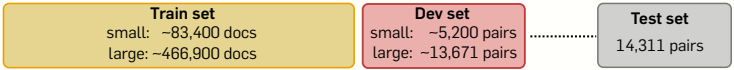

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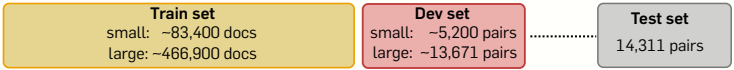

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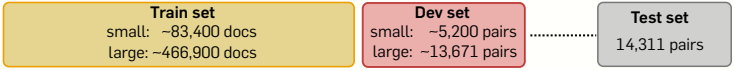

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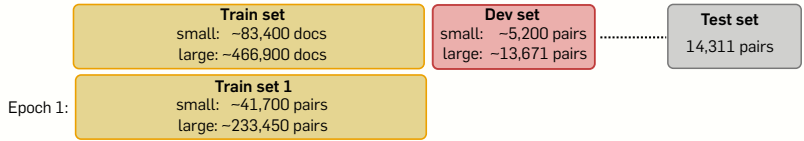

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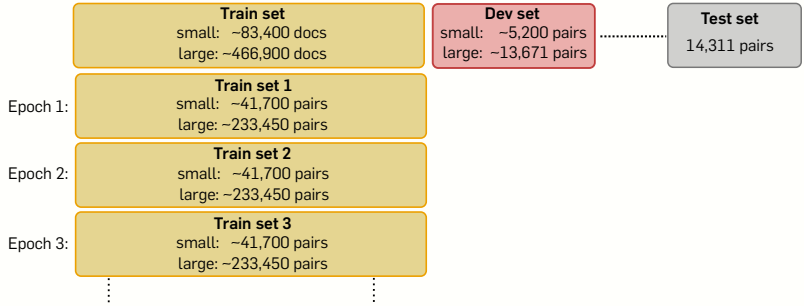

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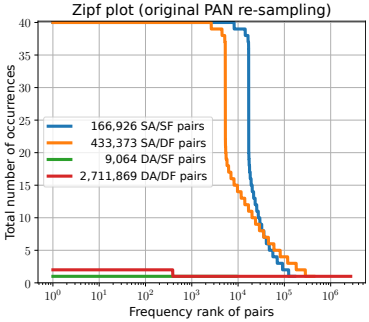
Improved re-sampling of document pairs[5]

- Problem: During training, our model repeatedly sees the same SA-pairs



[5] SA: same author, DA: different authors, SF: same fandom, DF: different fandoms

Improved re-sampling of document pairs[5]

- Modify the re-sampling of pairs w.r.t authorship and topical category

Algorithm 1 Re-sampling pairs

```
while authors with documents are available do
    for all authors do
        if r_1 ~ U[0, 1] < 1/2 then
            if r_2 ~ U[0, 1] < 1/2 then
                Try to sample SA/SF pair
            else
                Try to sample SA/DF pair
        else
            Try to sample a document for DA pairs
        Delete author from list if all documents are sampled
while two documents are available do
    if r_3 ~ U[0, 1] < 1/2 then
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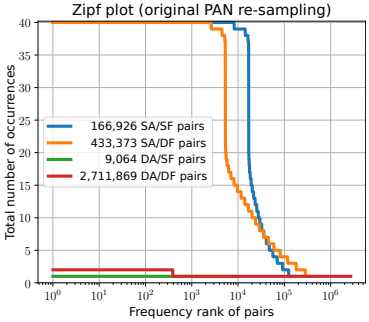
SA vs. DA

SA/SF vs. SA/DF

DA/SF vs. DA/DF



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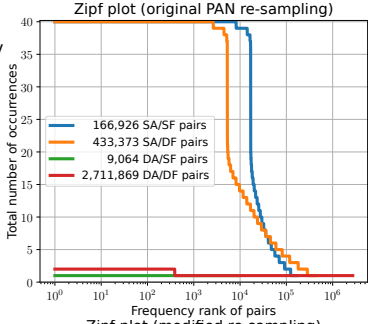

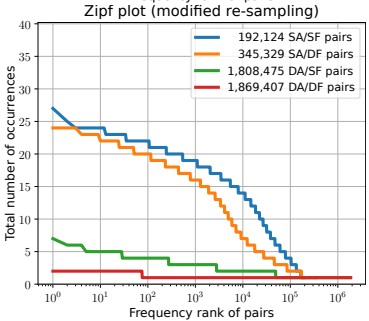

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Text preprocessing strategies: **(Overlapping) sliding windows with contextual prefixes**

- Construct a sentence-like unit consisting of tokens that are grammatically linked

' Yes , Master Luke , ' Rey says , a little surprised . ' How did you know ? ' ' You 're very skilled . Not just skilled . Not just natural talent , but practiced skill .

<Star Wars> ' Yes , Master Luke , ' <UNK> says , a little surprised .

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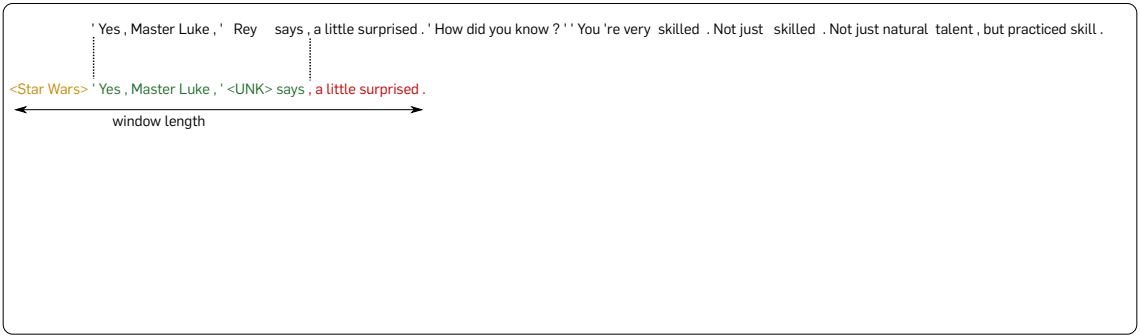

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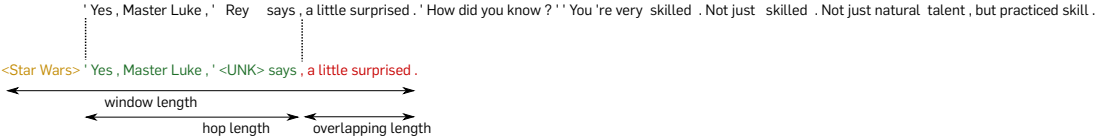

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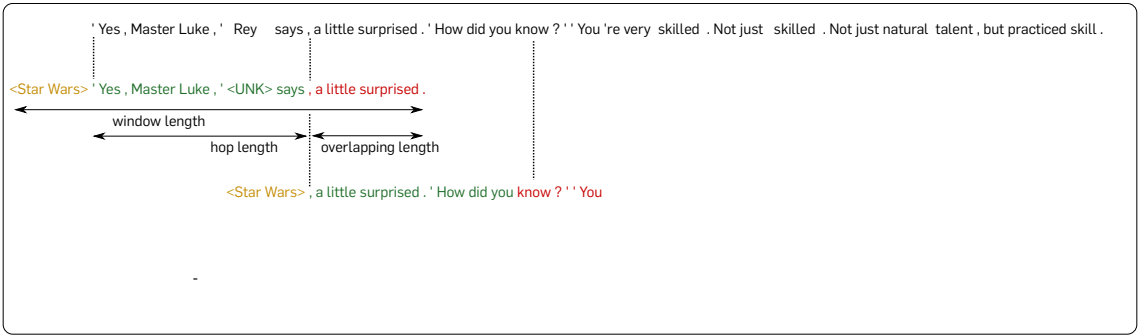

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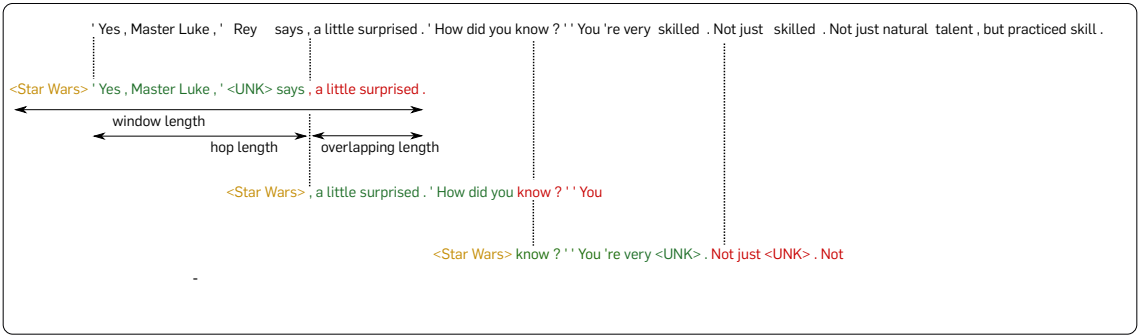

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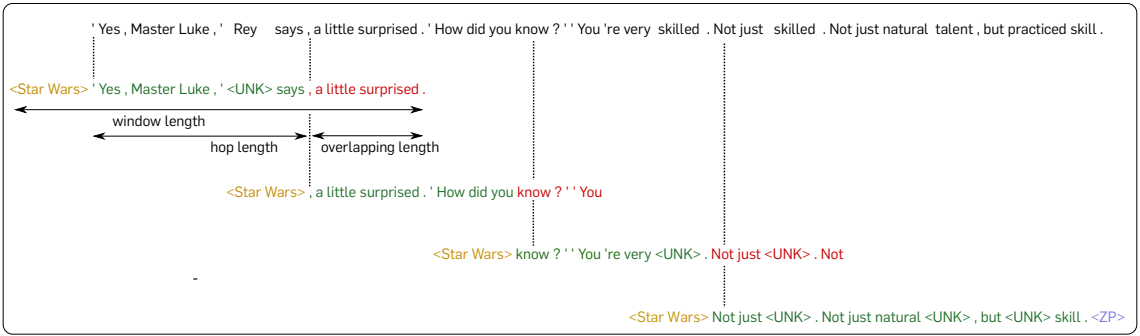

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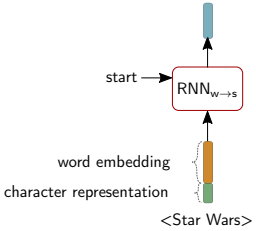

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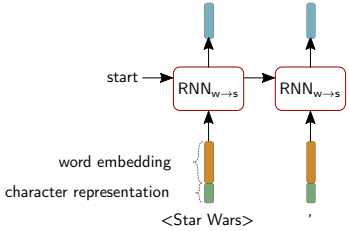

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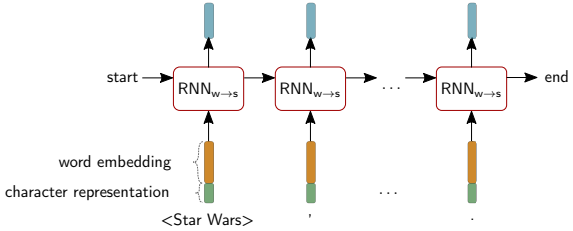

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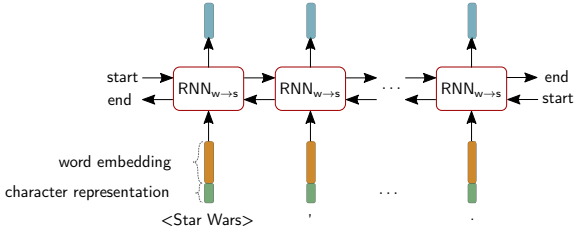

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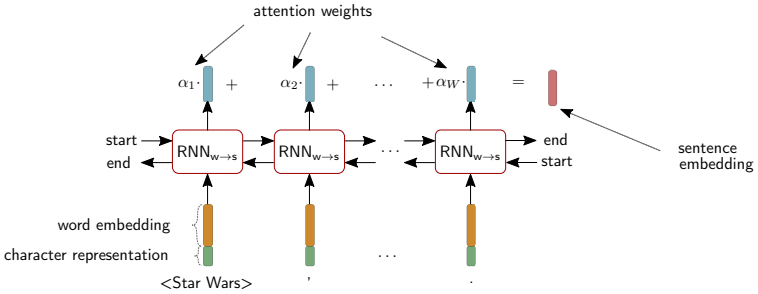

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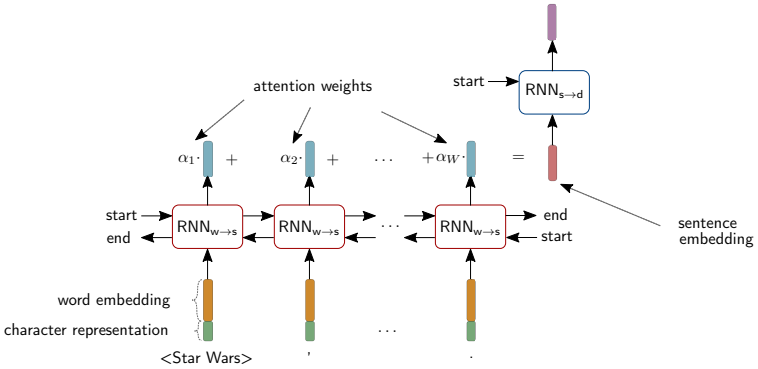

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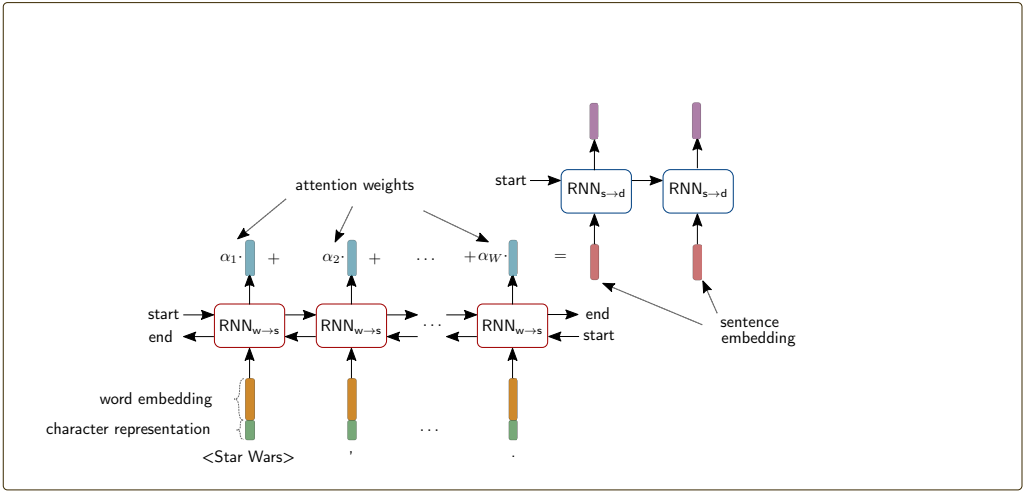

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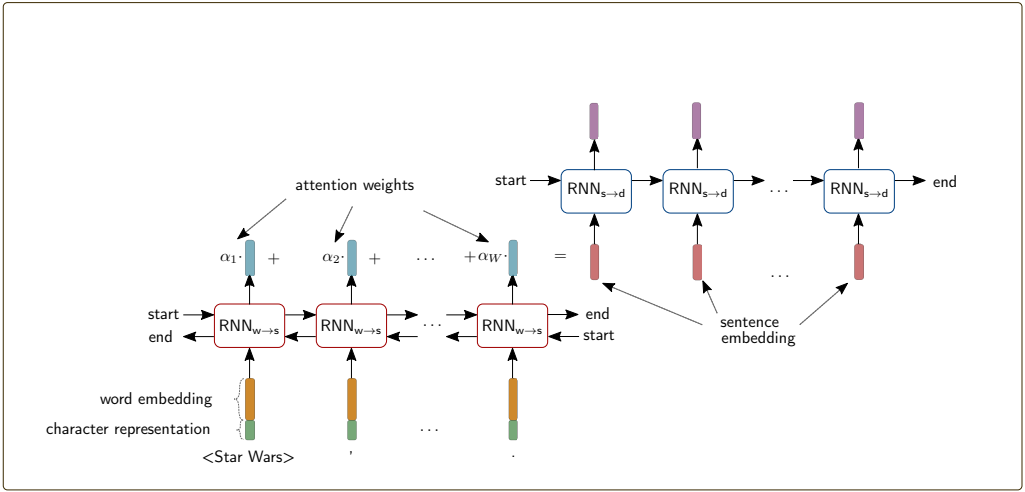

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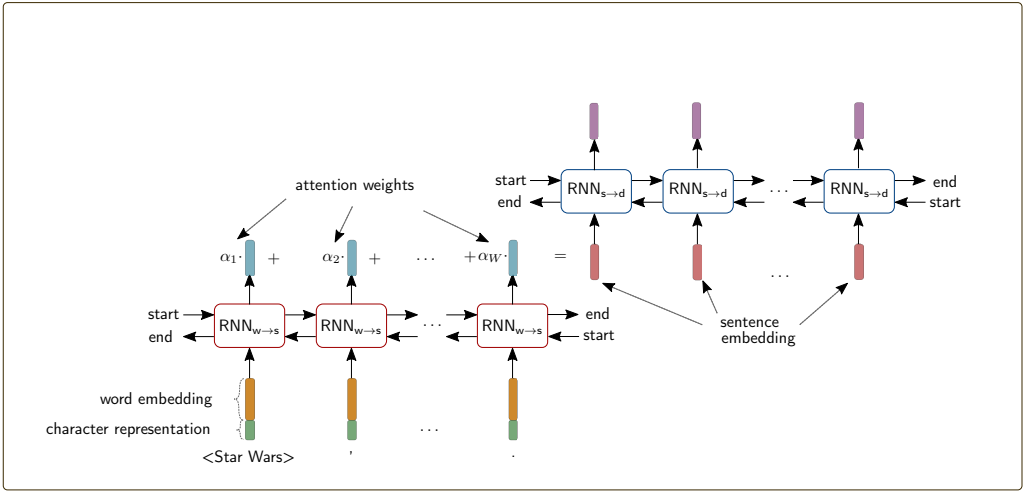

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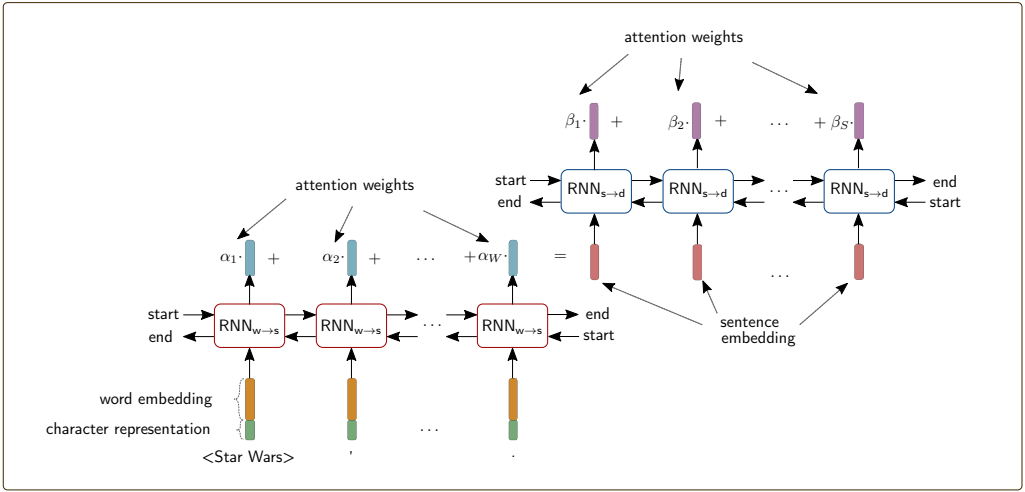

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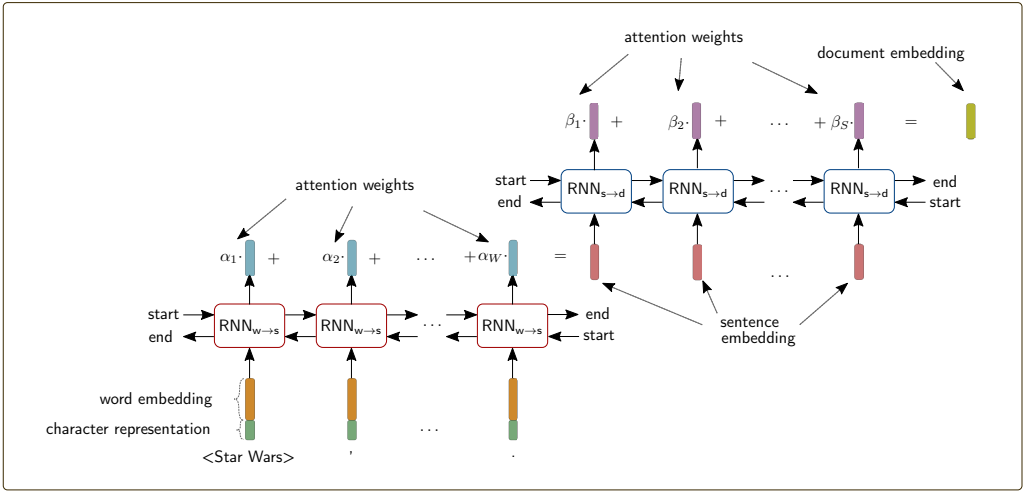

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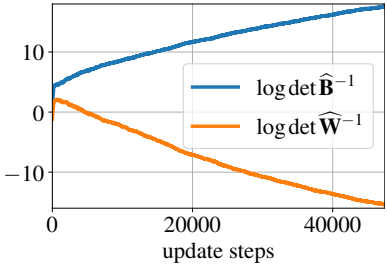

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- Verification score:

$$\Pr(\mathcal{H}_s|\boldsymbol{y}_1, \boldsymbol{y}_2) = \frac{\Pr(\mathcal{H}_s)\, p(\boldsymbol{y}_1, \boldsymbol{y}_2|\mathcal{H}_s)}{\Pr(\mathcal{H}_s)\, p(\boldsymbol{y}_1, \boldsymbol{y}_2|\mathcal{H}_s) + \Pr(\mathcal{H}_d)\, p(\boldsymbol{y}_1, \boldsymbol{y}_2|\mathcal{H}_d)} \approx \frac{p(\boldsymbol{y}_1, \boldsymbol{y}_2|\mathcal{H}_s)}{p(\boldsymbol{y}_1, \boldsymbol{y}_2|\mathcal{H}_s) + p(\boldsymbol{y}_1, \boldsymbol{y}_2|\mathcal{H}_d)}$$

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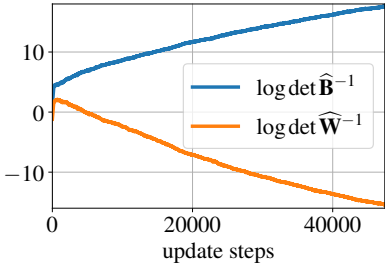
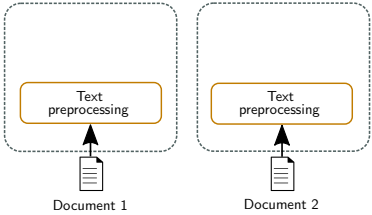


Combine binary cross-entropy and contrastive loss (Hu, Lu, and Tan 2014)



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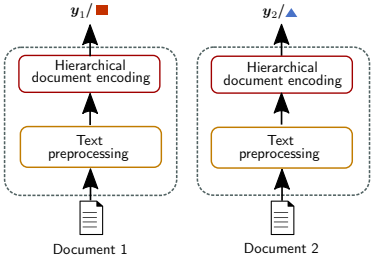

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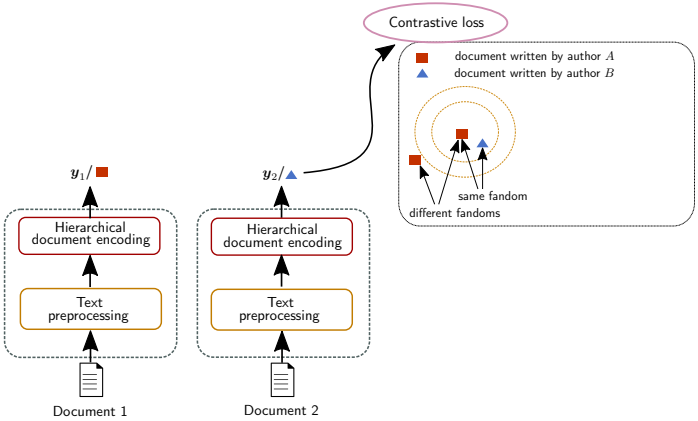

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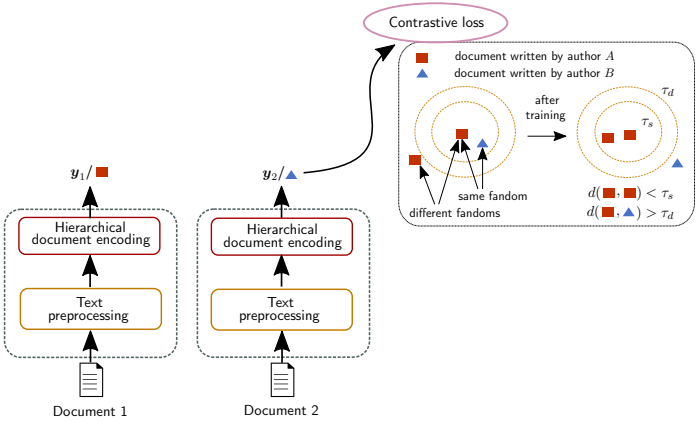

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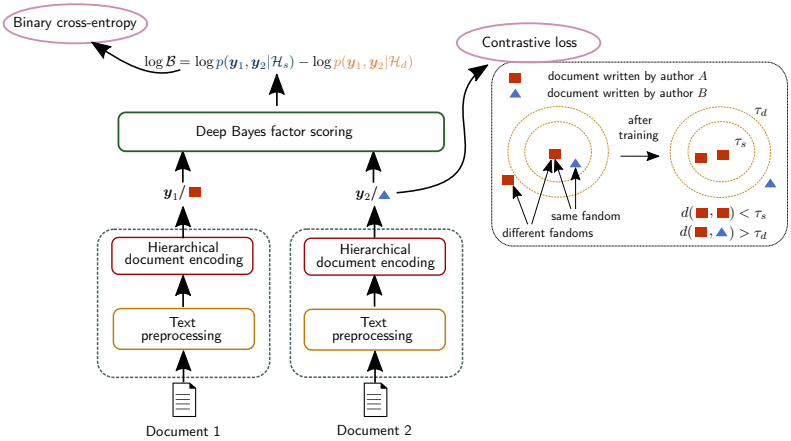

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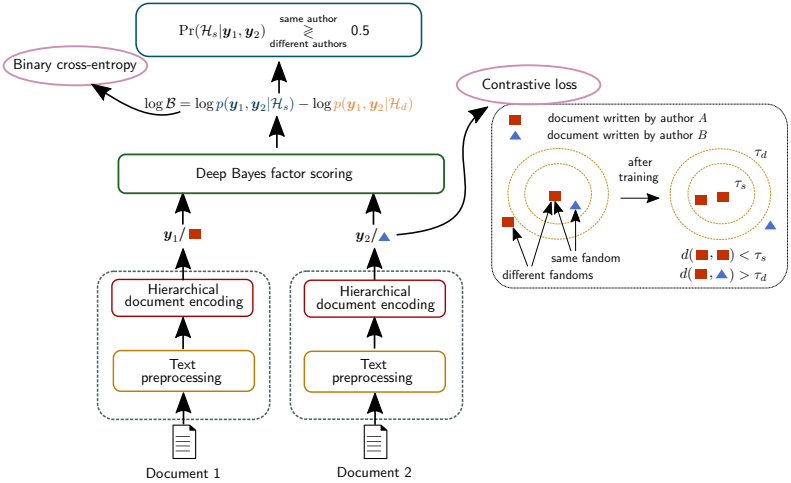

Evaluation results[7]

- Early-bird scores for dev set (small dataset)

		train set	evaluation	AUC	c@1	f_05_u	F1	overall
1	early-bird	small	dev set	0.964	0.919	0.916	0.932	0.933

[7] Colours represent the same models/runs

Evaluation results[7]

- Early-bird scores for test set ⇒ The model seems to generalize on the test set ☺

		train set	evaluation	AUC	c@1	f_05_u	F1	overall
1	early-bird	small	dev set	0.964	0.919	0.916	0.932	0.933
2	early-bird	small	test set	0.923	0.861	0.857	0.891	0.883

[7] Colours represent the same models/runs

Evaluation results[7]

- Best single runs for small/large datasets (at this step we introduced the contextual prefixes)

		train set	evaluation	AUC	c@1	f_05_u	F1	overall
1	early-bird	small	dev set	0.964	0.919	0.916	0.932	0.933
2	early-bird	small	test set	0.923	0.861	0.857	0.891	0.883
3	single	small	dev set	0.975	0.943	0.921	0.951	0.948
4	single	large	dev set	0.983	0.950	0.944	0.954	0.958

[7] Colours represent the same models/runs

Evaluation results[7]

- Ensembles that take the averaged vote from three independently trained "single" models

		train set	evaluation	AUC	c@1	f_05_u	F1	overall
1	early-bird	small	dev set	0.964	0.919	0.916	0.932	0.933
2	early-bird	small	test set	0.923	0.861	0.857	0.891	0.883
3	single	small	dev set	0.975	0.943	0.921	0.951	0.948
4	single	large	dev set	0.983	0.950	0.944	0.954	0.958
5	ensemble	small	dev set	0.977	0.942	0.938	0.946	0.951
6	ensemble	large	dev set	0.985	0.955	0.940	0.959	0.960

[7] Colours represent the same models/runs

Evaluation results[7]

- Results for ensembles on test set (including non-answers)

		train set	evaluation	AUC	c@1	f_05_u	F1	overall
1	early-bird	small	dev set	0.964	0.919	0.916	0.932	0.933
2	early-bird	small	test set	0.923	0.861	0.857	0.891	0.883
3	single	small	dev set	0.975	0.943	0.921	0.951	0.948
4	single	large	dev set	0.983	0.950	0.944	0.954	0.958
5	ensemble	small	dev set	0.977	0.942	0.938	0.946	0.951
6	ensemble	large	dev set	0.985	0.955	0.940	0.959	0.960
7	ensemble	small	test set	0.940	0.889	0.853	0.906	0.897
8	ensemble	large	test set	0.969	0.928	0.907	0.936	0.935

[7] Colours represent the same models/runs

Evaluation results[7]

- Model 9 = model 6/8 without defining non-answers

		train set	evaluation	AUC	c@1	f_05_u	F1	overall
1	early-bird	small	dev set	0.964	0.919	0.916	0.932	0.933
2	early-bird	small	test set	0.923	0.861	0.857	0.891	0.883
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6	ensemble	large	dev set	0.985	0.955	0.940	0.959	0.960
7	ensemble	small	test set	0.940	0.889	0.853	0.906	0.897
8	ensemble	large	test set	0.969	0.928	0.907	0.936	0.935
9	ensemble	large	test set	0.969	0.912	0.917	0.920	0.930

[7] Colours represent the same models/runs

Final ranking of the submitted approaches[8]

RANK	TEAM	TRAINING DATASET	AUC	C@1	F0.5U	F1-SCORE	OVERALL
1	boenninghoff20	large	0.969	0.928	0.907	0.936	0.935
2	weerasinghe20	large	0.953	0.880	0.882	0.891	0.902
3	boenninghoff20	small	0.940	0.889	0.853	0.906	0.897
4	weerasinghe20	small	0.939	0.833	0.817	0.860	0.862
5	halvani20b	small	0.878	0.796	0.819	0.807	0.825
6	kipnis20	small	0.866	0.801	0.815	0.809	0.823
7	araujo20	small	0.874	0.770	0.762	0.811	0.804
8	niven20	small	0.795	0.786	0.842	0.778	0.800
9	gagala20	small	0.786	0.786	0.809	0.800	0.796
10	araujo20	large	0.859	0.751	0.745	0.800	0.789
11	baseline (naive)	small	0.780	0.723	0.716	0.767	0.747
12	baseline (compression)	small	0.778	0.719	0.703	0.770	0.742
13	ordonez20	large	0.696	0.640	0.655	0.748	0.685
14	faber20	small	0.293	0.331	0.314	0.262	0.300

[8] https://pan.webis.de/clef20/pan20-web/author-identification.html

Looking forward to the PAN 2021 open-set AV challenge

- Simply splitting authors/fandoms into two disjoint groups

number of authors (train):	142,605
number of authors (dev):	29,543
number of fandoms (train):	1,120
number of fandoms (dev):	412

Looking forward to the PAN 2021 open-set AV challenge

- Simply splitting authors/fandoms into two disjoint groups
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- Simply splitting authors/fandoms into two disjoint groups
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- New challenging dev set:
  - It contains only "unseen" authors/fandoms
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number of authors (train):	**142,605**
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- New challenging dev set:
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  - Cross-fandom orthogonality: Only SA/DF and DA/SF pairs
- First results (without non-answers and contextual prefixes):

number of authors (train):	142,605
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	vocabulary size (characters)	vocabulary size (words)	hop_length	train word embeddings	AUC	c@1	f_05_u	F1	overall
1	150	15,000	25	YES	0.962	0.898	0.902	0.897	0.915
2	150	5,000	25	YES	0.969	0.907	0.909	0.906	**0.923**
3	150	50,000	25	YES	0.947	0.855	0.893	0.841	0.884
4	150	15,000	30	YES	0.961	0.896	0.903	0.894	0.913
5	750	15,000	25	YES	0.964	0.902	0.902	0.901	0.917
6	150	15,000	25	NO	0.962	0.896	0.905	0.894	0.914
7	150	5,000	25	NO	0.961	0.895	0.902	0.893	0.912

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Acknowledgement

Big thanks to the PAN2020-AV-team for organizing the shared task! ☺

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