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Text/Non-text Classification in Online Handwritten Documents with Recurrent Neural Networks

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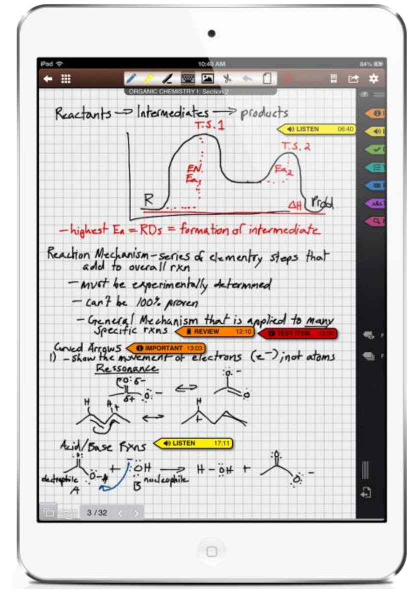
Background – Trends

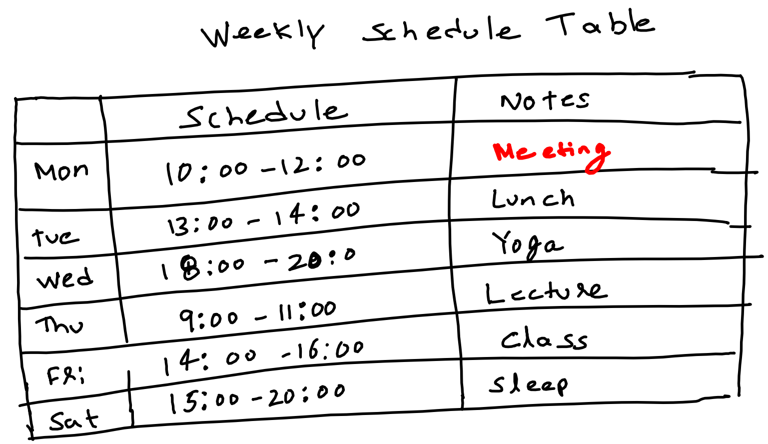
- **Pen-based, touch-based devices/applications have become popular.**



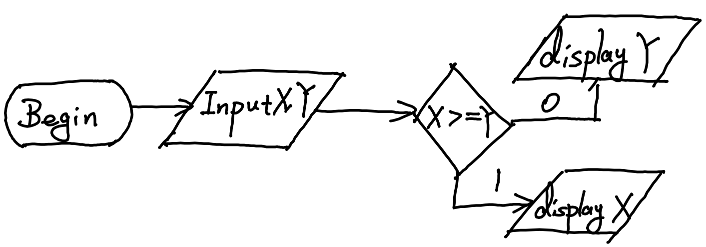
- **People can create notes, make diagrams, draw sketches on their mobile devices.**

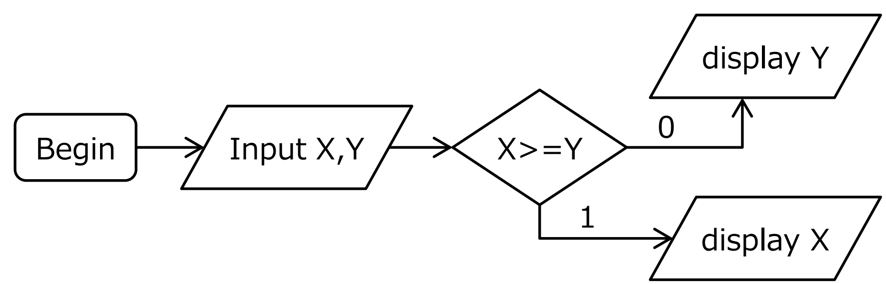
Background – Needs

- **Text search on hand-written notes, schedules,...**



- **Hand-drawn sketch (diagrams, flowcharts,…) recognition/interpretation.**

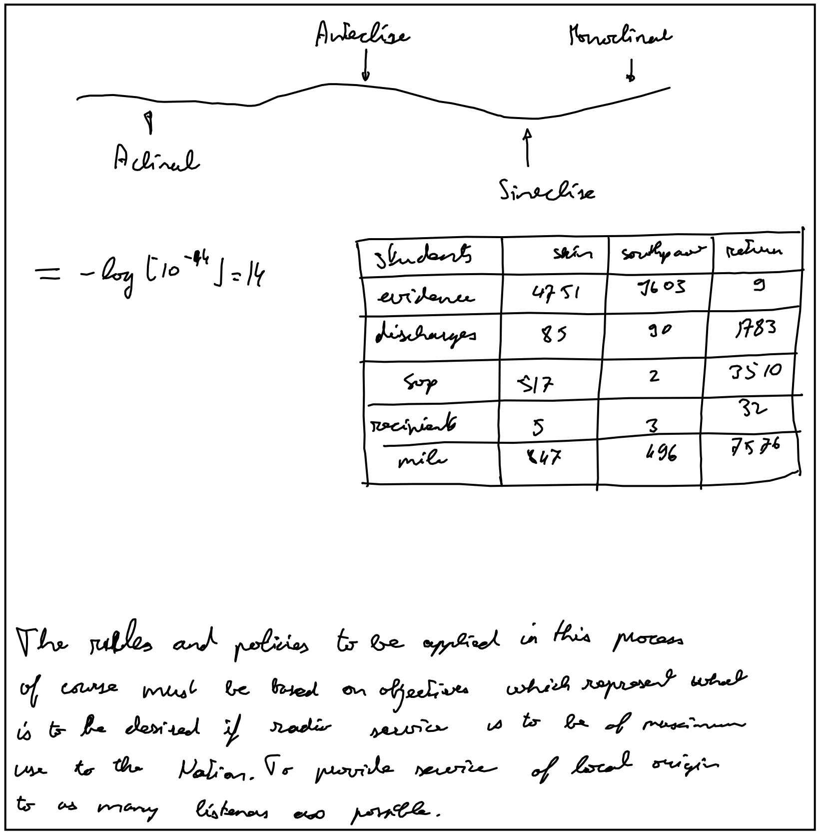


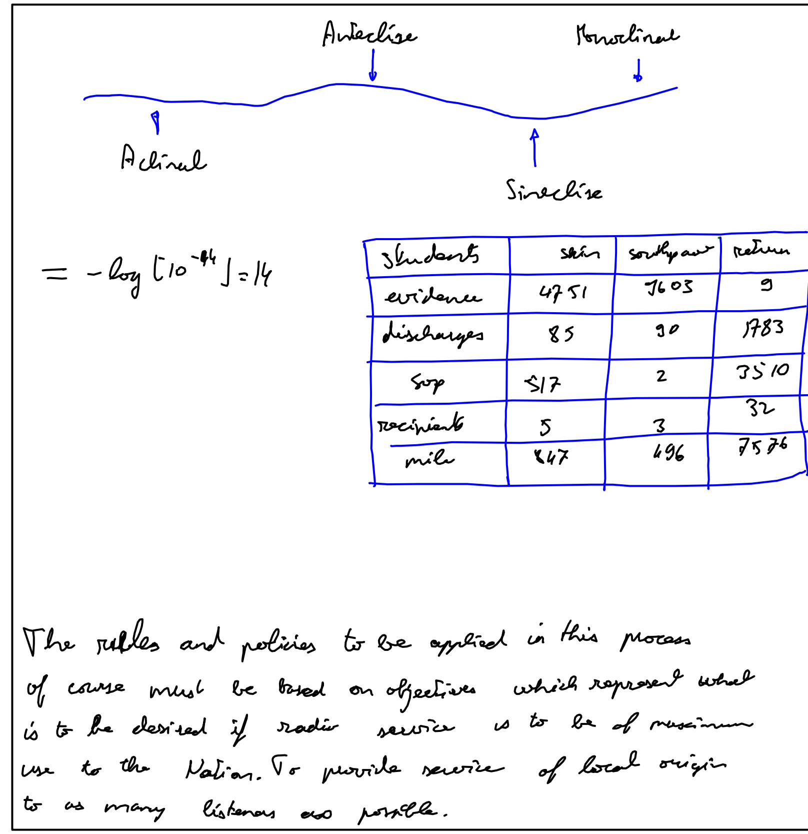


Ref. to presentation of “**Recognition System for On-line Sketched Diagrams**” by Martin Bresler, on Thursday, *Session 9, 10:00 ~ 10:20*

Text/Non-text Classification

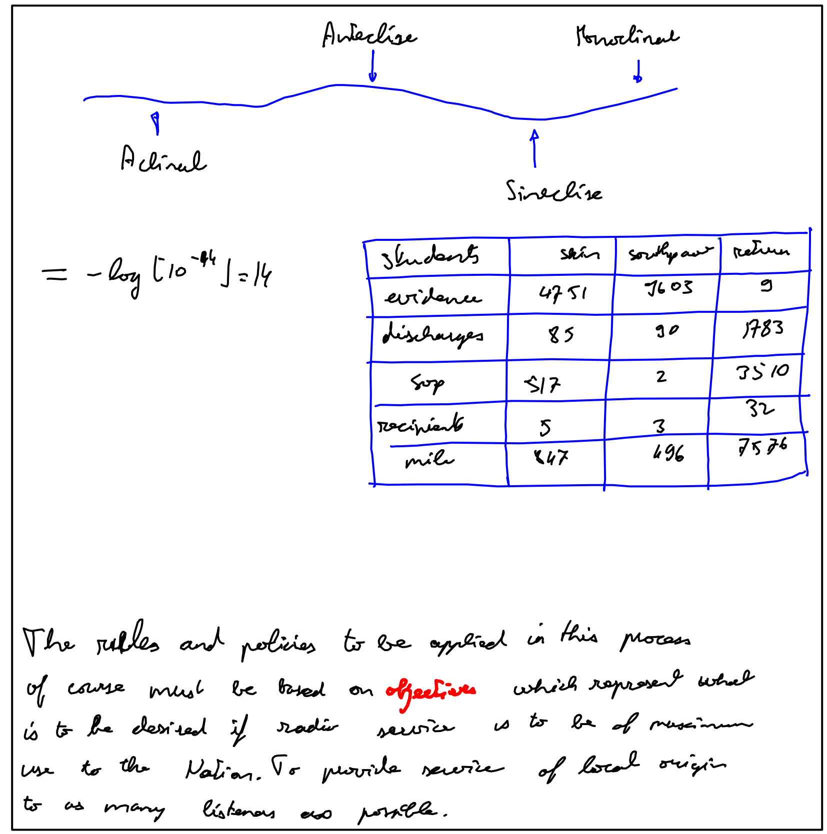
- **To classify handwritten ink strokes into two categories: text and non-text.**





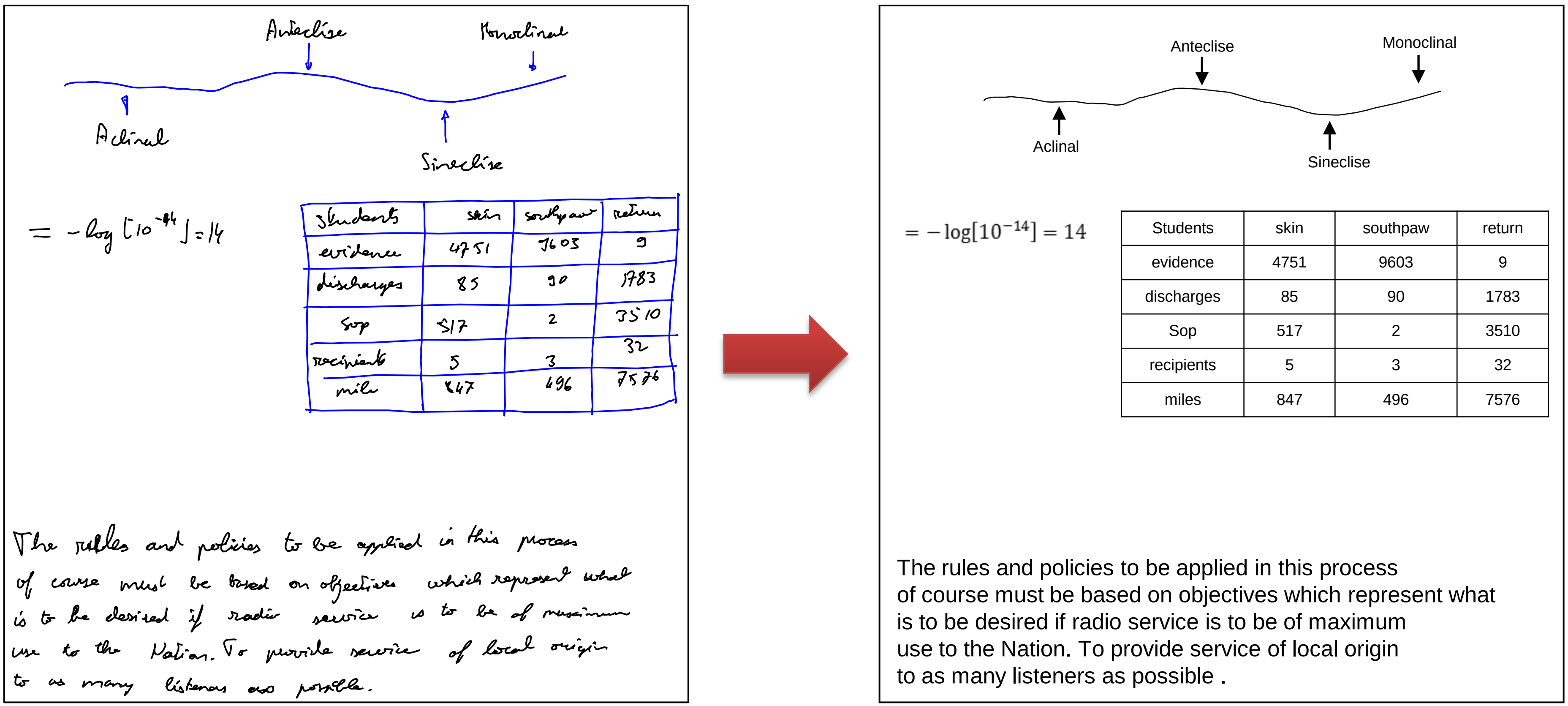
Text/Non-text Classification

- **It can be used as a preprocessing step for text search, text recognition, or diagram interpretation.**



Text/Non-text Classification

- It can be used as a **preprocessing** step for text search, **text recognition**, or **diagram interpretation**.



Related work

- **Two approaches**
  - Context-integrated classification: single stroke classification (SVM, MLP) → context integration (HMM, MRF, CRF)
  - Sequence classification by using BLSTM.

- **Remarkable results**

Publication	Method	Data Set	Accuracy
Zhou and Liu [3]	SVMs + HMM SVMs + MRF	Kondate	94.48 **96.61**
Indermuhle et al. [8]	BLSTM	IAMonDo	97.01
Delaye et al. [4]	SVMs + CRF	IAMonDo	**97.23**

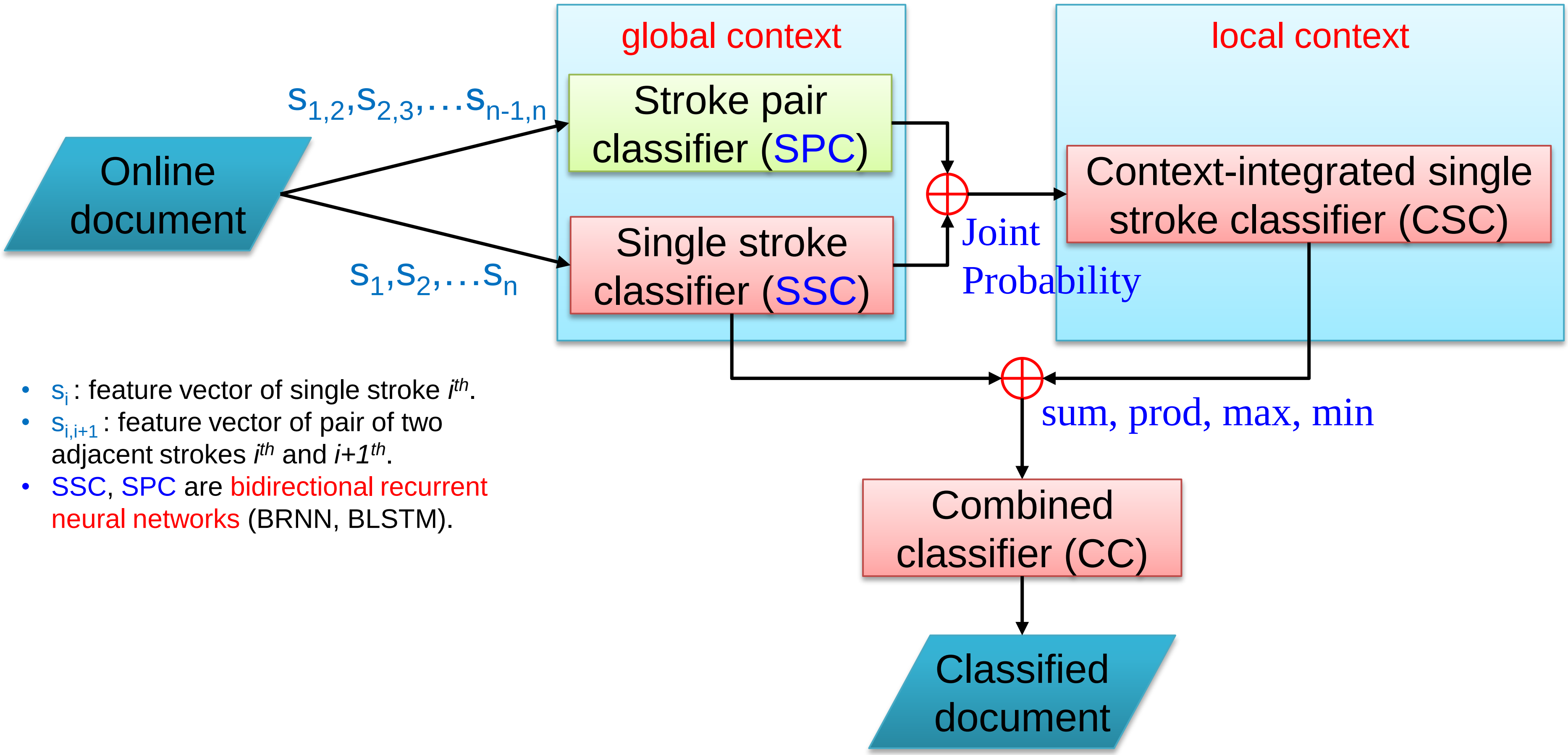
Consideration

- **In order for text/non-text classification to be practical, it should be highly accurate and quick.**

- **State-of-the-art performances are not satisfied.**
  - Current accuracies are only about 97%.
  - SVMs + MRF/CRF methods are slow because of SVMs.
  - BLSTM method is quick but not accurate since it considers interactions between points only.

Outline of our method

- **It's a context-integrated sequence classification method using both global and local contexts.**



- s_i : feature vector of single stroke i^{th}.
- $s_{i,i+1}$: feature vector of pair of two adjacent strokes i^{th} and $i+1^{th}$.
- SSC, SPC are bidirectional recurrent neural networks (BRNN, BLSTM).

Global context model

- **Make use of bidirectional recurrent neural networks to gain access to the global context of the whole document.**
- **To transcribe a sequence of feature vectors to a sequence of labels.**

	Single stroke classifier (SSC)	Stroke pair classifier (SPC)
Input (feature)	Unary (extracted from each stroke)	Binary (extracted from pair of two temporally adjacent strokes)
Output (label)	2 categories • text (T) • non-text (N)	3 categories • text:text (TT) • text:non-text (TN) or non-text:text (NT) • non-text:non-text (NN)
Sequence length	N $S_1, S_2, \ldots S_n$	N-1 $S_{1,2}, S_{2,3}, \ldots S_{n-1,n}$

N: number of strokes in document

Local context model

- **Use marginal distribution to integrate context of neighboring strokes.**

$$P(X = x) = \sum_{y} P(X = x | Y = y) P(Y = y)$$

Probability of a stroke *i*th being text is calculated by

1. **Preceding Model (PM)**

$$\cdots\ s_{i-1} \rightarrow s_i \rightarrow s_{i+1}\ \cdots$$

$$P_{PM}(T_i) = P\left(TT_{i,i-1}\right)P(T_{i-1}) + P(TN_{i,i-1})P(N_{i-1})$$

2. **Succeeding Model (SM)**

$$\cdots\ s_{i-1} \leftarrow s_i \leftarrow s_{i+1}\ \cdots$$

$$P_{SM}(T_i) = P\left(TT_{i,i+1}\right)P(T_{i+1}) + P(TN_{i,i+1})P(N_{i+1})$$

3. **Bidirectional Model (BM)**

$$\cdots\ s_{i-1} \leftrightarrow s_i \leftrightarrow s_{i+1}\ \cdots$$

$$P_{BM}(T_i) = P_{PM}(T_i) + P_{SM}(T_i)$$

Combined classifier

■ Use four basic combination rules

- ◆ Sum rule (SUM)

$$l_i^* = argmax\left\{\sum_{k=1}^{K} f_k(l_i|s_i), l_i \in \{\mathrm{T},\mathrm{N}\}\right\}$$

- ◆ Product rule (PROD)

$$l_i^* = argmax\left\{\prod_{k=1}^{K} f_k(l_i|s_i), l_i \in \{\mathrm{T},\mathrm{N}\}\right\}$$

- ◆ Max rule (MAX)

$$l_i^* = argmax\left\{max_{k=1}^{K} f_k(l_i|s_i), l_n \in \{\mathrm{T},\mathrm{N}\}\right\}$$

- ◆ Min rule (MIN)

$$l_i^* = argmax\left\{min_{k=1}^{K} f_k(l_i|s_i), l_n \in \{\mathrm{T},\mathrm{N}\}\right\}$$

where $K = 2$,

- $f_1(l_i|s_i)$ is the probability distribution of l_i calculated by the single stroke classifier (SSC),
- $f_2(l_i|s_i)$ is one of the three probability distributions of l_i calculated by the context-integrated single stroke classifier (CSC).

Experiment

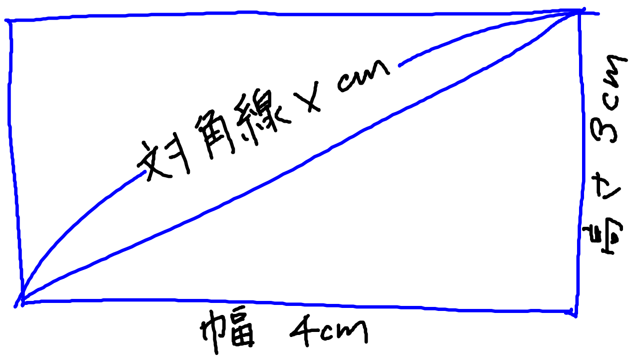
Data

Database	Subset	# pages	# strokes	% T	% N
Kondate (Japanese)	*Training*	210	41,190	83.53	16.47
	Validation	100	18,525	84.89	15.11
	Testing	359	71,846	85.44	14.56
IAMonDo (English)	*Training*	403	143,350	80.96	19.04
	Validation	200	68,726	83.60	16.40
	Testing	203	70,927	81.26	18.74

Evaluation

- Single stroke classifiers (SSCs)
- Stroke pair classifiers (SPCs)
- Context-integrated single stroke classifiers (CSCs)
- Combined classifiers (CCs)
- Computational time

Data samples – Kondate



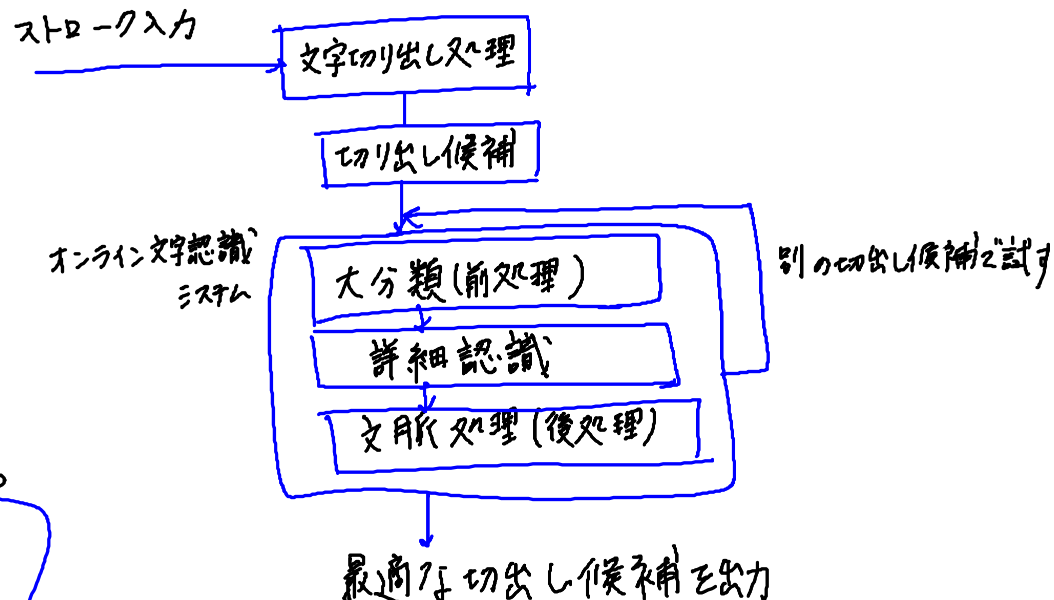


図5 オンライン枠なし文字認識システムの大まかな流れ

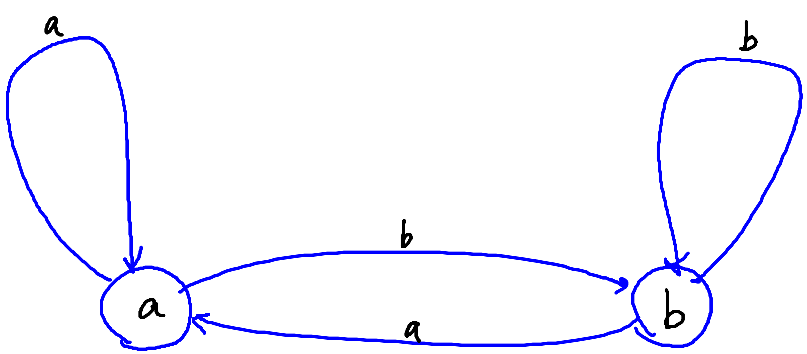
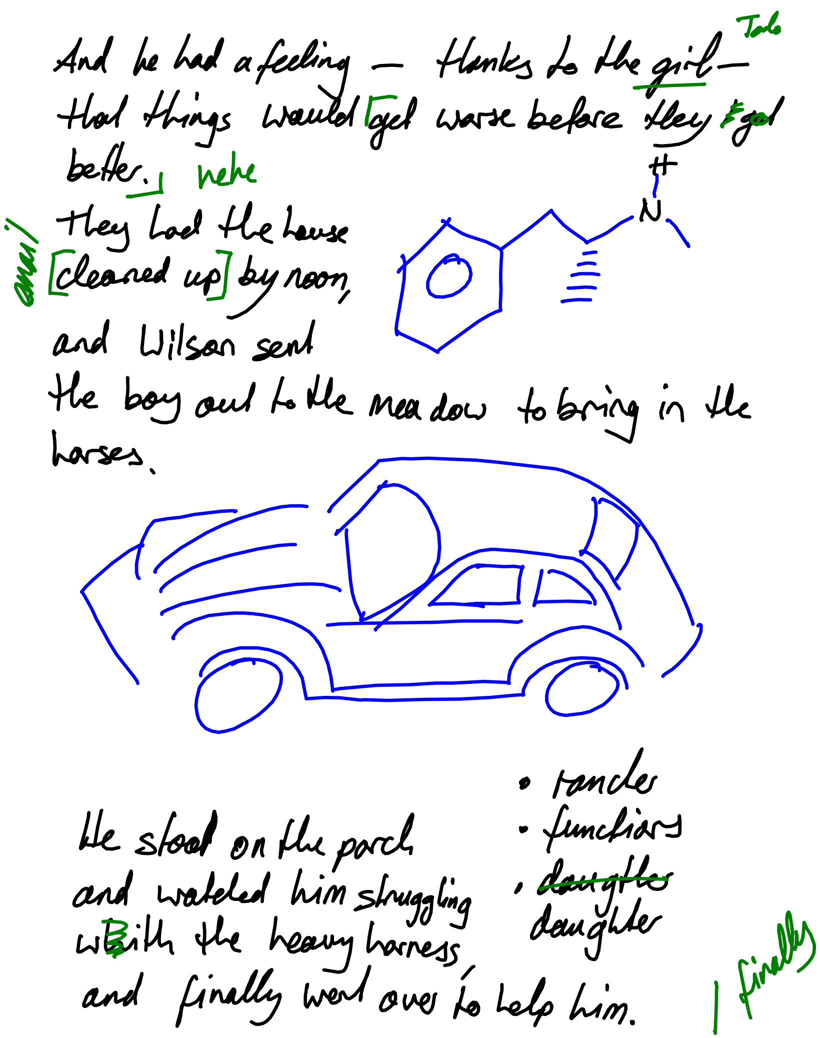
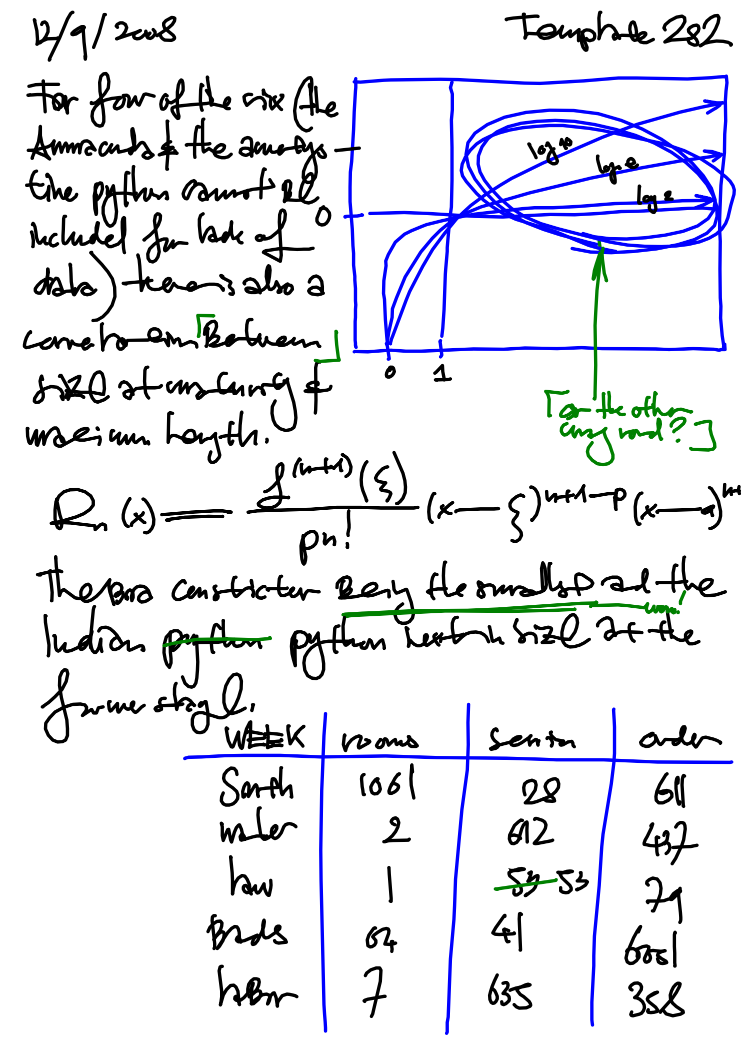


図1 バイグラムの確率有限オートマトンによる表現

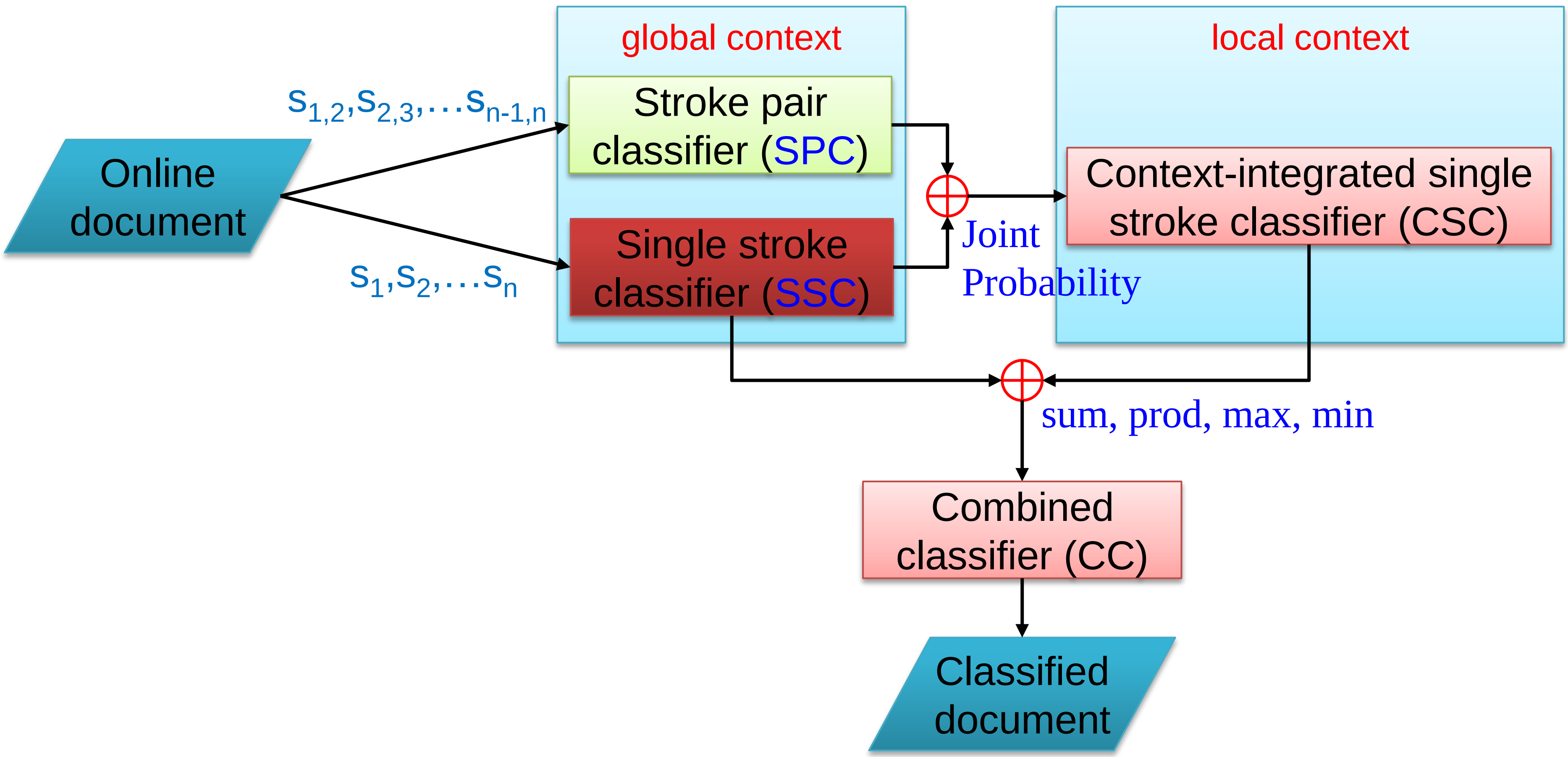
Data samples – IAMonDo





Experimental result

■ Single stroke classifiers (SSCs)



Experimental result

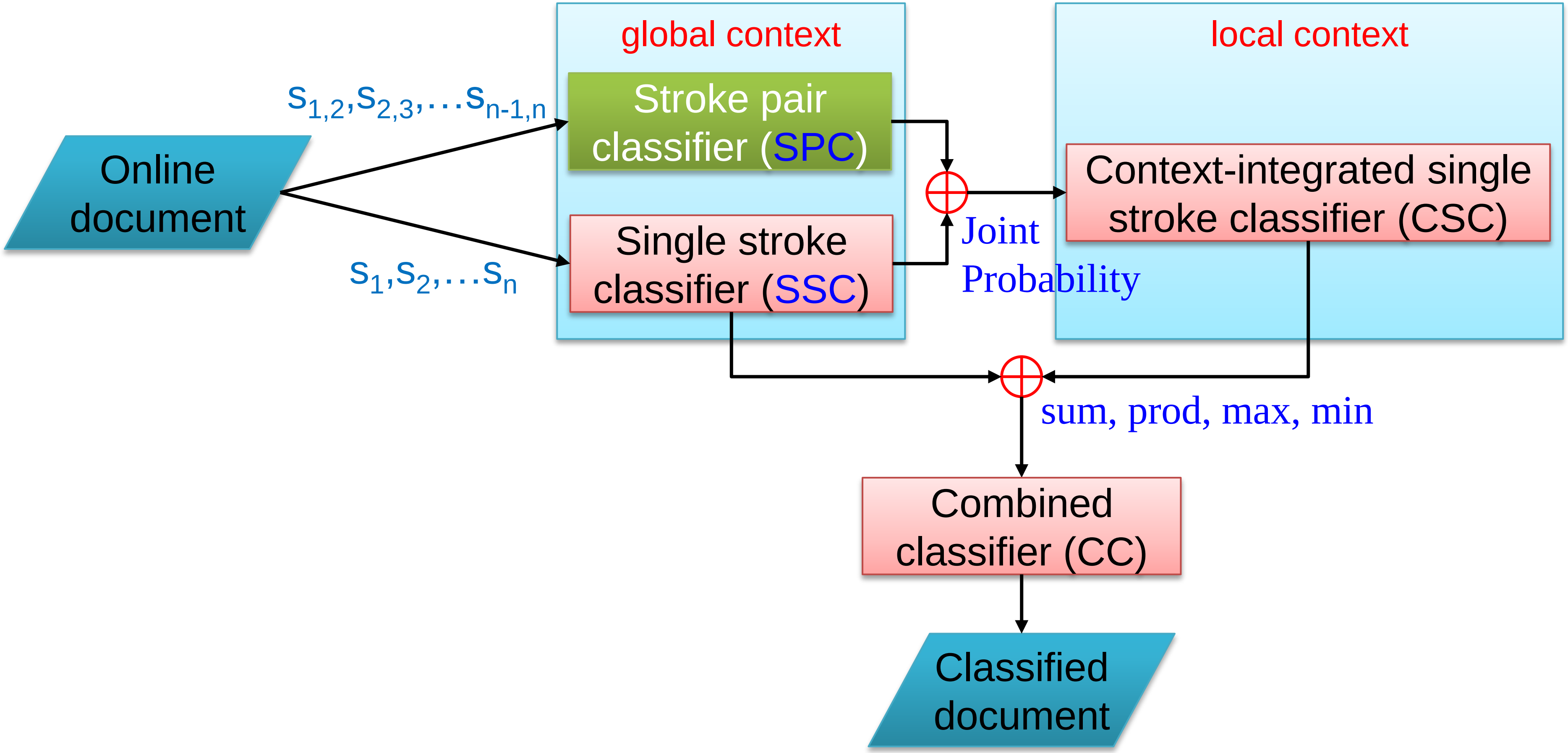
■ Single stroke classifiers (SSCs)

Database	Classifier	Accuracy (%)			Total time (s)
		Overall *(average (min ~ max))*	Text *(average)*	Non-text *(average)*	
Kondate (Japanese)	*SSC11_RNN*	95.39 (94.33～96.36)	98.37	77.90	0.38
	SSC11_LSTM	96.13 (95.48～96.57)	98.53	82.05	1.53
	SSC19_RNN	96.43 (94.65～97.45)	98.58	83.79	0.39
	SSC19_LSTM	**97.01** (95.68～**97.62**)*	**98.71**	**87.08**	1.56
IAMonDo (English)	*SSC11_RNN*	95.62 (94.76～96.28)	97.87	85.87	0.36
	SSC11_LSTM	96.41 (96.15～96.73)	98.15	88.87	1.49
	SSC19_RNN	96.62 (96.15～97.09)	98.13	90.09	0.37
	SSC19_LSTM	**96.93** (96.65～**97.34**)**	**98.38**	**90.63**	1.50

* Zhou and Liu [3]: 96.61%
** Delaye et al. [4]: 97.23%

Experimental result

■ Stroke pair classifiers (SPCs)



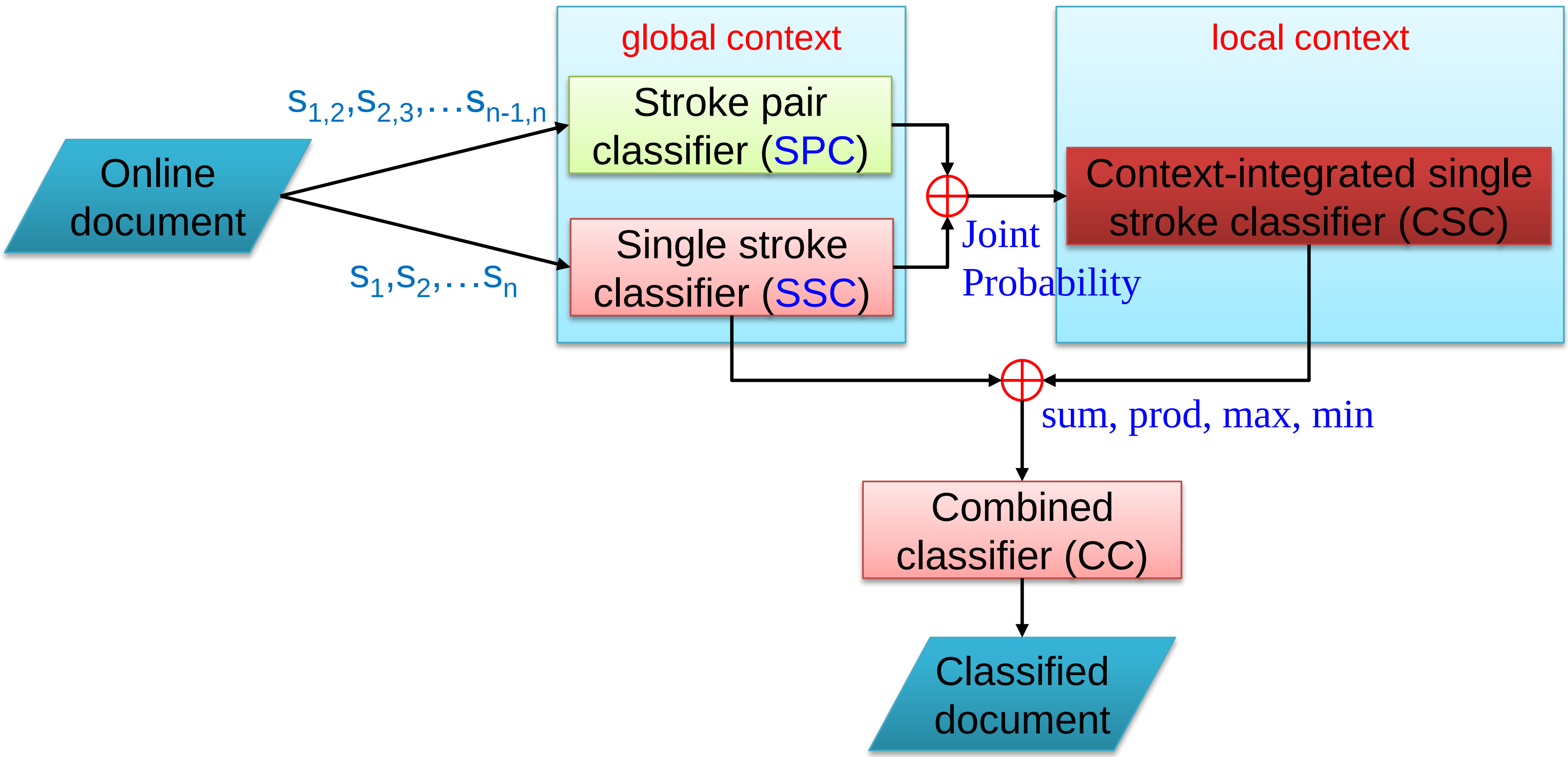
Experimental result

■ Stroke pair classifiers (SPCs)

Database	Classifier	Accuracy (%)				Total time (s)
		Overall *(average (min ~ max))*	**TT** *(average)*	**TN** *(average)*	**NN** *(average)*	
Kondate (Japanese)	*SPC_RNN*	95.54 (93.00～96.79)	98.16	68.16	87.46	0.38
	SPC_LSTM	**96.71** (95.71～**97.38**)	**98.63**	**80.65**	**89.35**	1.51
IAMonDo (English)	*SPC_RNN*	92.90 (90.55～94.52)	**97.86**	28.04	82.65	0.53
	SPC_LSTM	**94.46** (93.67～**95.03**)	97.72	**47.47**	**88.55**	1.48

Experimental result

■ **Context-integrated single stroke classifiers (CSCs)**



Experimental result

■ Context-integrated single stroke classifiers (CSCs)

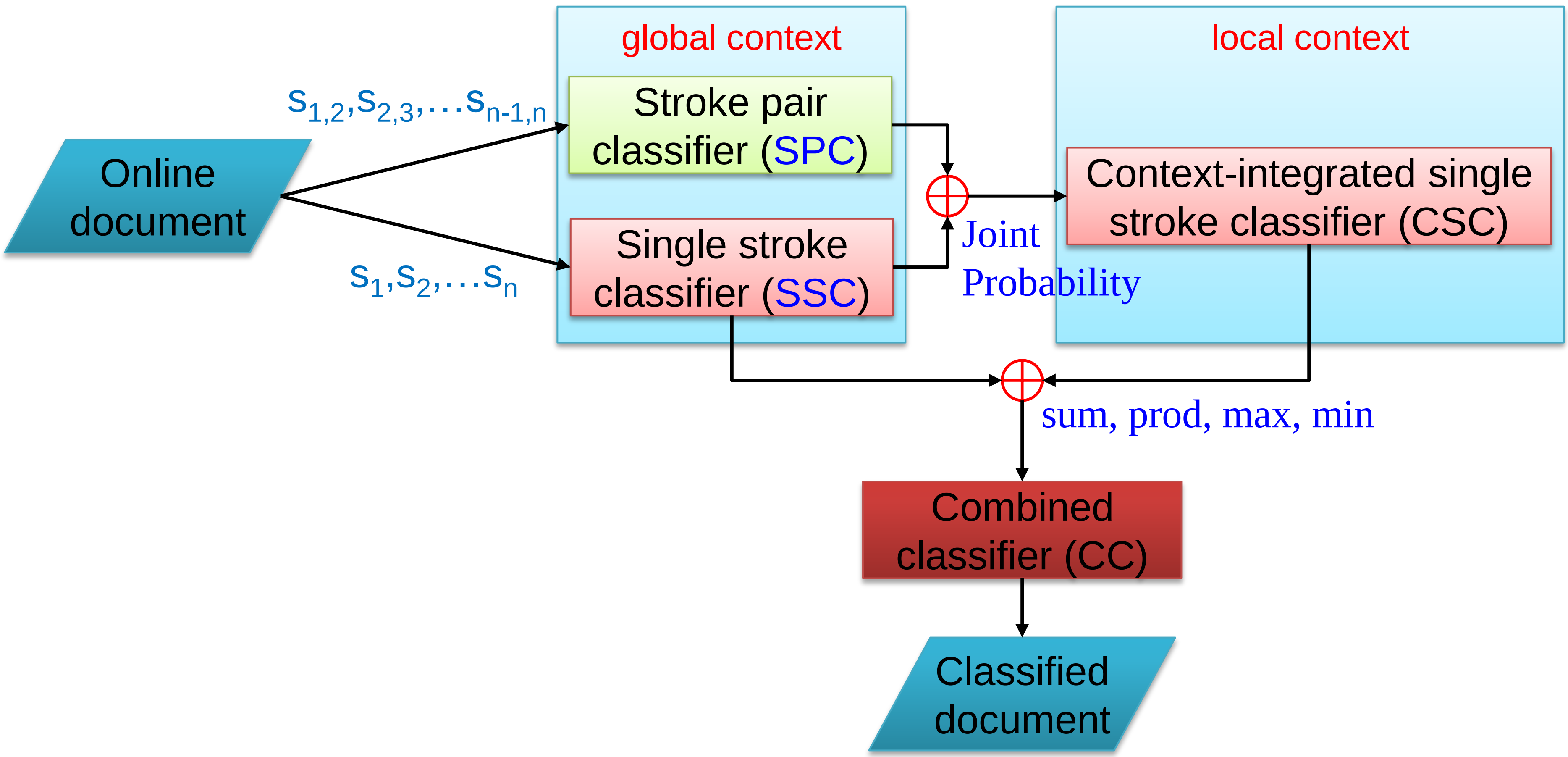
Database	SPC Classifier	SPC Accuracy (%)	SSC Classifier	SSC Accuracy (%)	CSC Accuracy (%)		
					PM	SM	BM
Kondate (Japanese)	*SPC_RNN*	96.79	*SSC11_RNN*	96.36	97.13	97.13	**97.72**
			SSC19_RNN	97.45	97.43	97.27	**97.91**
	SPC_LSTM	97.38	*SSC11_LSTM*	96.57	97.55	97.59	**98.18**
			SSC19_LSTM	**97.62**	97.96	97.89	**98.43***
IAMonDo (English)	*SPC_RNN*	94.52	*SSC11_RNN*	96.28	96.26	96.29	**96.69**
			SSC19_RNN	**97.09**	96.51	96.50	96.89
	SPC_LSTM	95.03	*SSC11_LSTM*	96.73	96.63	96.59	**97.03**
			SSC19_LSTM	**97.34****	96.85	96.75	**97.19**

* Zhou and Liu [3]: 96.61%

** Delaye et al. [4]: 97.23%

Experimental result

■ Combined classifiers (CCs)



Experimental result

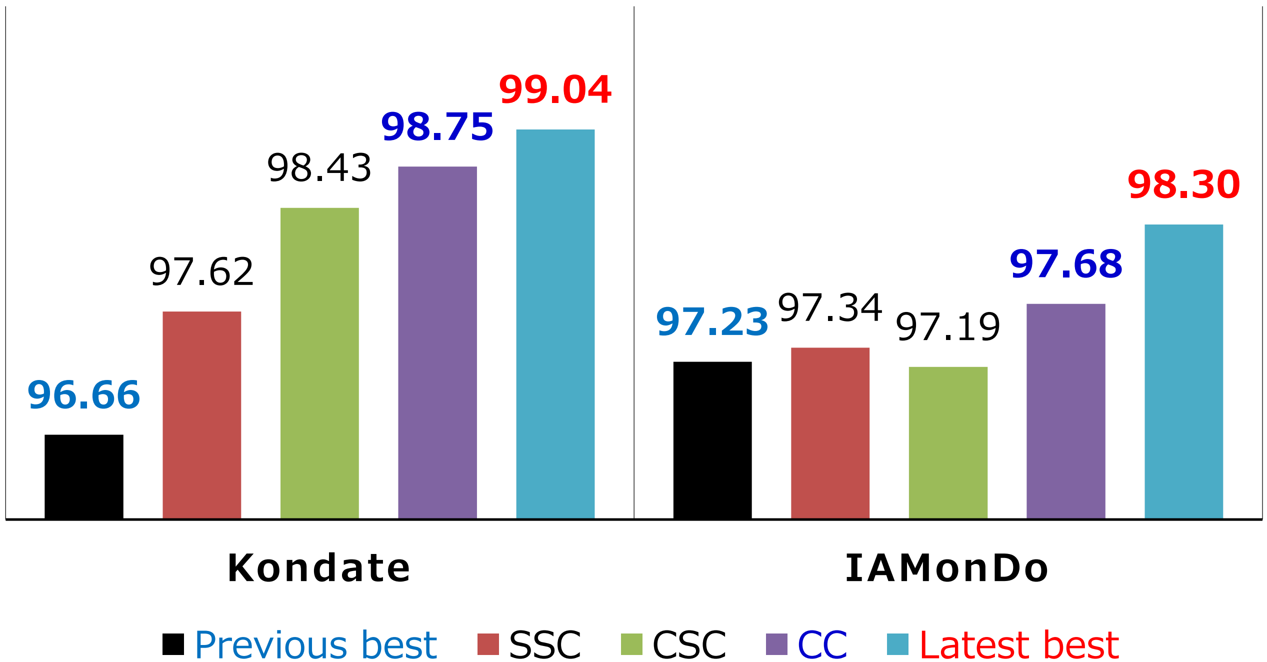
■ Combined classifiers (CCs)

Database	Type	SSC Accuracy (%)	CSC Accuracy (%)	CC Accuracy (%)			
				SUM	PROD	MAX	MIN
Kondate (Japanese)	*11_RNN*	96.57	98.18	97.72	**98.23**	97.58	**98.29**
	19_LSTM	97.62	**98.43**	98.38	**98.73**	98.28	**98.75***
IAMonDo (English)	*11_RNN*	96.73	97.03	97.19	**97.32**	97.10	**97.36**
	19_LSTM	**97.34**	97.19	97.55	**97.65**	97.50	**97.68****

* Zhou and Liu [3]: 96.61%
** Delaye et al. [4]: 97.23%

Experimental result

■ Summary



■ Computational time

Time (s)	Kondate 359 pages	IAMonDo 203 pages
Feature Extraction (Unary + Binary)	1.1	4.6
Classification (Single stroke + Stroke pair)	3.2	3.2
Context Integration	0.01	0.01
Total	**4.3**	**7.8**
Average (per page)	**0.012**	**0.038***

* Delaye et al. [4]: 1.53 (s)

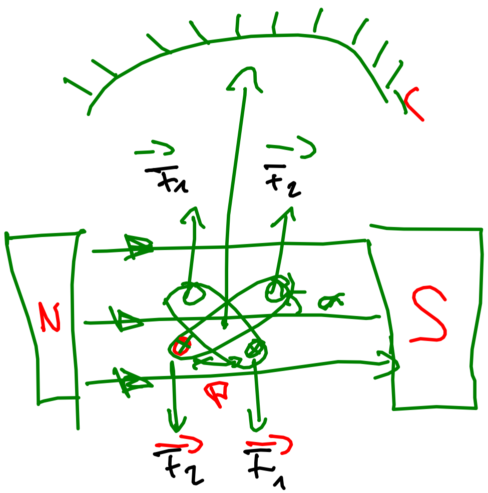
Conclusion

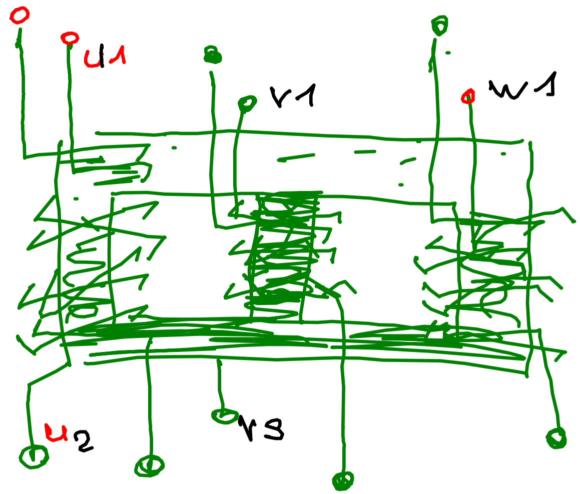
- **We proposes a context-integrated sequence classification method for text/non-text classification in online handwritten documents.**
  - Recurrent neural networks for sequence classification.
  - Marginal distribution and simple combination rules (sum, prod, max, min) for context integration.

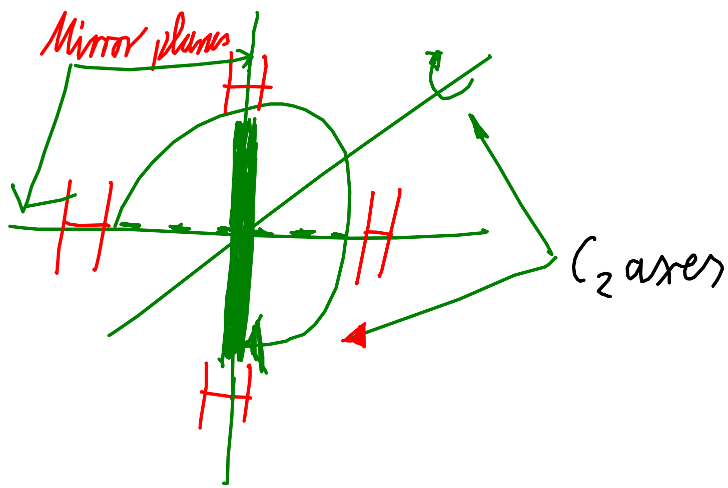
- **We achieves classification rates of 98.75% (99.04%) on Kondate and 97.68% (98.30%) on IAMonDo.**

Future work

- Solve these kinds of problems







Demo

if you requested