Reciprocal Feature Learning via Explicit and Implicit Tasks in Scene Text Recognition

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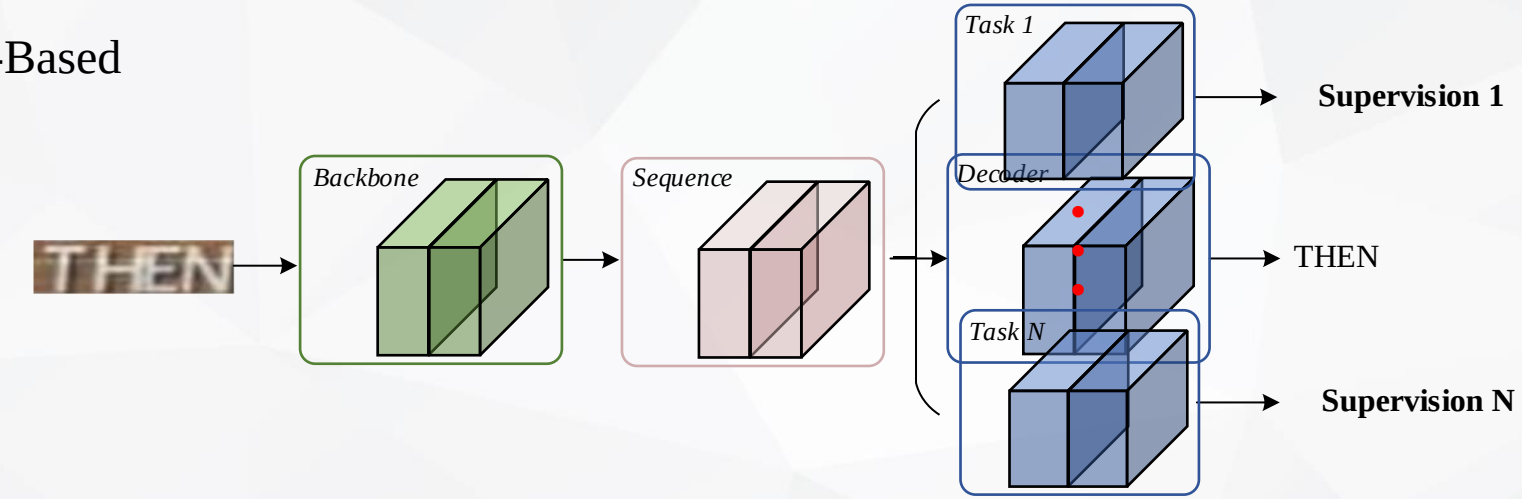
Content

- **Background**
- **Method**
- **Experiment**

Background

Scene Text Recognition Feat Single-Task Learning

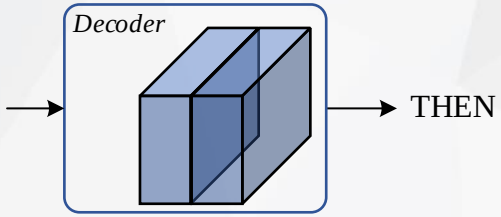
- CTC-Based
- Attention-Based

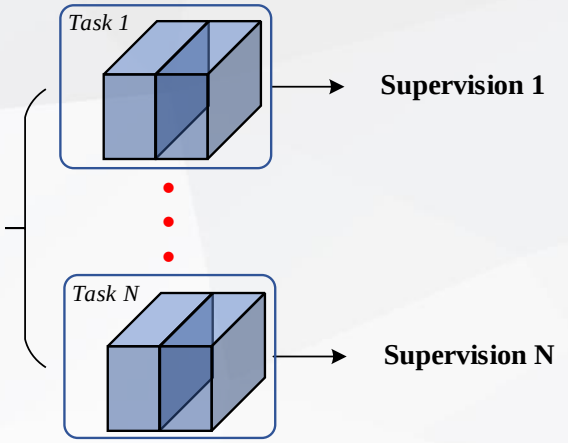


Scene Text Recognition Feat Multi-Task learning

- Additional information from another task or detailed supervision
- Exploiting original tasks and supervision

Background





✵ Drawback of current solution

- ➢ Single Task solution
  - ❖ **Limited Performance**
  - ❖ **Add extra annotations**
- ➢ Multi-Task solution
  - ❖ **Immature Technology Application**
  - ❖ **Ignore the relation between tasks**
  - ❖ **Task competition**

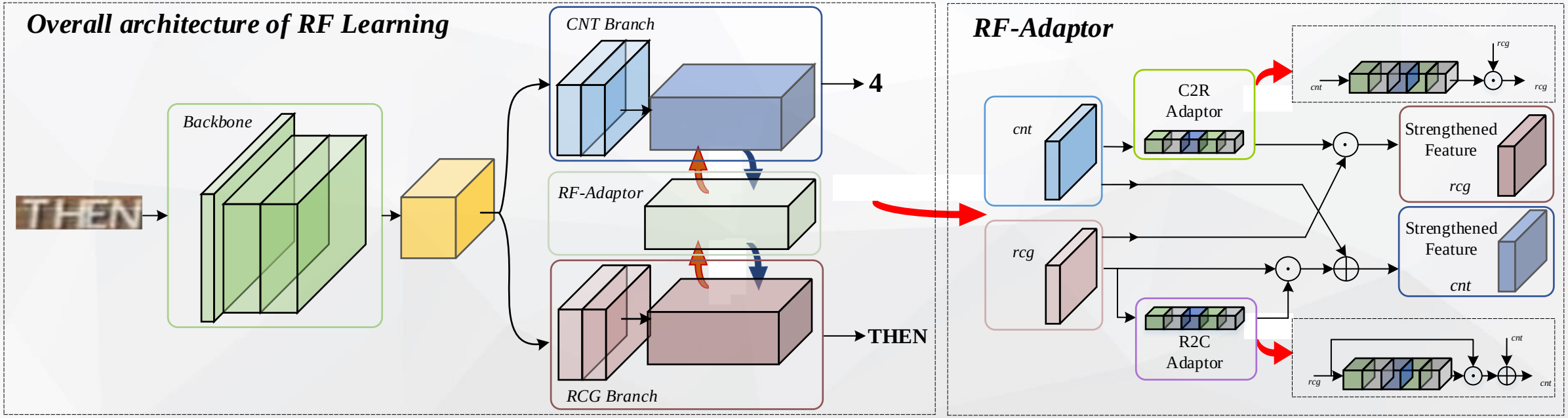
✵ Motivation

- ➢ **Excavate implicit information from existing annotations to training a auxiliary task**
- ➢ **Excavate and utilize the relation between tasks to improve the performance**

Method

Overall Architecture

- Backbone
- Character Counting Branch (CNT)
- Text Recognition Branch (RCG)
- Reciprocal Feature Adaptor (RF-Adaptor)

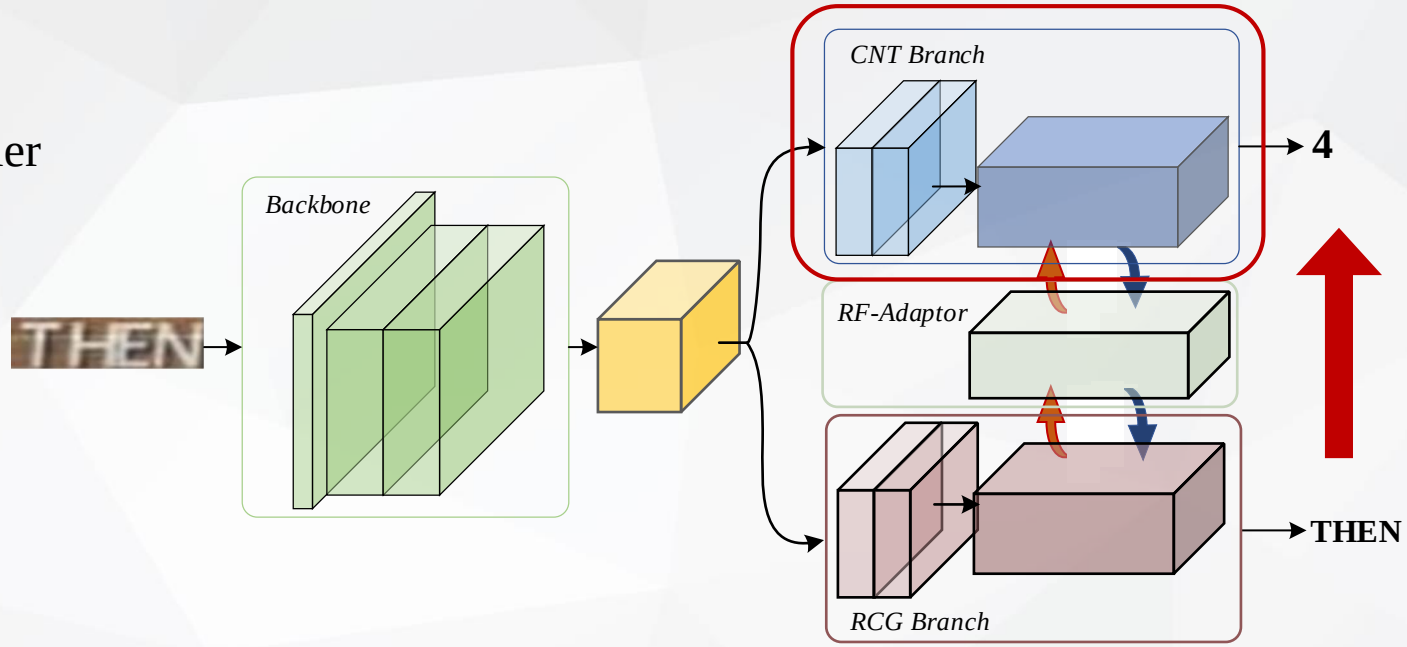


Method

✵ Character Counting Branch

Text is a is **hierarchically** information carrier

Then
- T: 1 h : 1 e : 1 n : 1
- T Th The Then
- **4**



Text length is a facilitated information in text information and correlate to the text recognition task

$$L_{cnt} = \begin{cases} MSE(\hat{y}_{cnt}, y_{cnt}) & if\ Regression \\ CrossEntropy(\hat{y}_{cnt}, y_{cnt}) & if\ Classfication \end{cases}$$

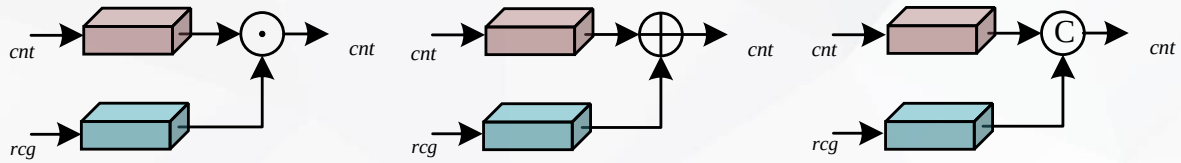
$$Metric = \begin{cases} RMSE = \sqrt{\frac{1}{N}\sum_{I=1}^{N}(\hat{c}_i - c_i)^2} \\ relRMSE = \sqrt{\frac{1}{N}\sum_{I=1}^{N}\frac{(\hat{c}_i - c_i)^2}{c_i + 1}} \end{cases}$$

Method

❋ Reciprocal Feature Adaptor

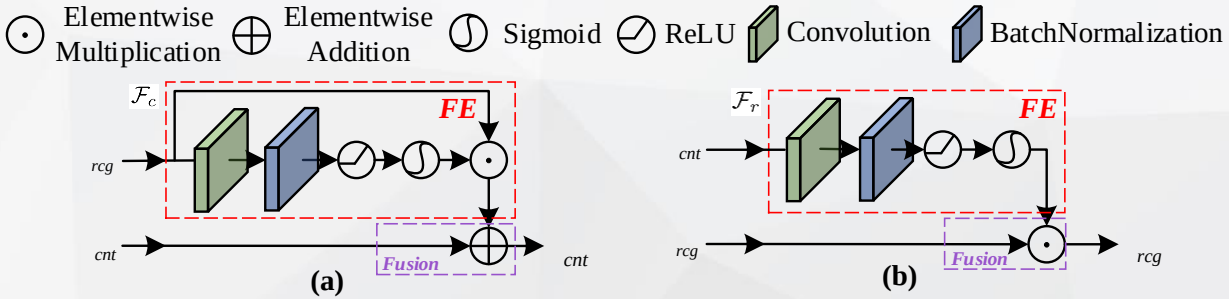
Transfer the bi-directional complementary data from one to the other, assembling features and adapting to task

➢ Feature Fusion

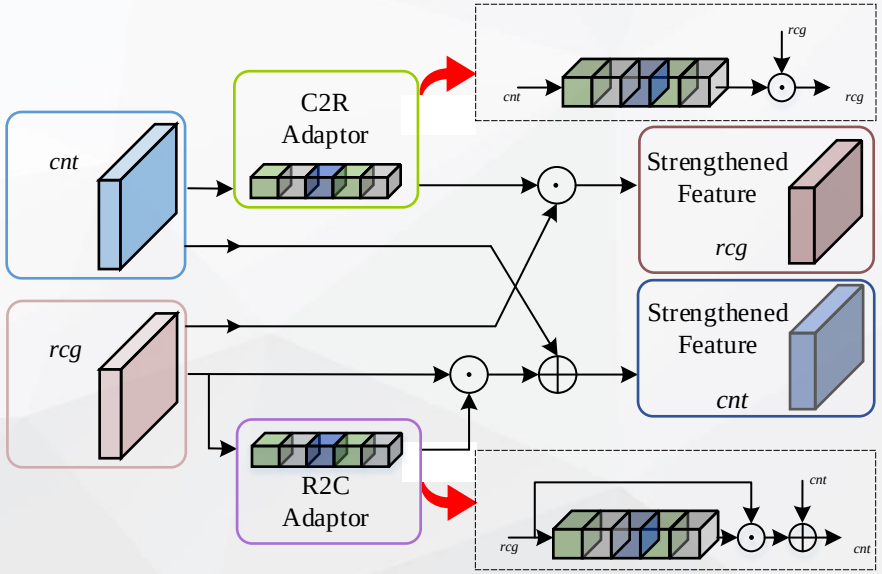


- ❖ RCG contains more information than CNT, replenish information via ⊕
- ❖ CNT is feature selector like a learnable gate to suppress the noise via ⊙

➢ Feature Strengthen



- ❖ Apply different self-enhancement module to strengthen the feature



Experiment

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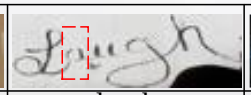
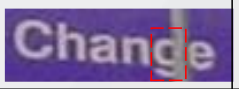
❋ Performance Summary

Compared with SOTA solution

Methods	Year	Training data	Benchmark							Avg. Acc	
			IIIT	SVT	IC03	IC13	IC15	SVTP	CT	Regular	Irregular
CRNN [27]	2016	MJ	78.2	80.8	89.4	-	-	-	-	-	-
AON [5]	2018	MJ+ST	87.0	82.8	91.5	-	-	73.0	76.8	-	-
NRTR [26]	2018	MJ+ST	90.1	**91.5**	94.7	-	79.4	**86.6**	80.9	-	82.3
ASTER [28]	2019	MJ+ST	93.4	89.5	94.5	91.8	-	78.5	79.5	92.3	-
TPS-Bilstm-Attn [1]	2019	MJ+ST	87.9	87.5	94.9	93.6	77.6	79.2	74.0	91.0	76.9
AutoSTR [40]∗	2020	MJ+ST	94.7	90.9	93.3	94.2	81.8	81.7	-	**93.2**	-
RobustScanner [39]†	2020	MJ+ST	**95.3**	88.1	-	-	-	79.5	**90.3**	-	-
Bilstm-Attn [1][3]	2019	MJ+ST	93.7	89.0	92.3	93.2	79.3	81.2	80.6	92.1	80.4
Bilstm-Attn *w.* RF-L	-	MJ+ST	94.1	88.6	94.9	**94.5**	**82.4**	82.0	82.6	93.0(+0.9)	**82.4**(+2.0)
DAN [35][4]	2020	MJ+ST	93.4	87.5	94.2	93.2	75.6	80.9	78.0	92.1	78.2
DAN *w.* RF-L	-	MJ+ST	94.0	87.7	93.6	93.5	76.7	84.7	77.8	92.2(+0.1)	79.7(+1.5)

Samples				
w.o RF-L	vll	gujara	lugh	souris
w. RF-L	evil	gujarat	laugh	solaris
Samples				
w.o RF-L	pipinang	alibabal	chance	refore
w. RF-L	ppinang	alibaba	change	before

Experiment

❋ Ablation Summary

❖ CNT Implementation Ablation

Methods	*w.o.* Class Balance		*w.* Class Balance	
	Regular[2]	Irregular	Regular	Irregular
CE	89.5	78.5	93.2	83.5
Regression	93.3	82.3	**94.6**	**84.5**

❖ CNT Implementation compared with ACE

Methods	Auxiliary		RCG Accuracy (%)				CNT RMSE			
	CNT	RCG	IIIT	SVT	IC03	IC15	IIIT	SVT	IC03	IC15
ACE			87.5	81.8	89.9	67.5	0.477	0.963	0.555	0.889
w. RCG (RF-L)		√	**88.4**	**83.8**	90.2	70.0	**0.323**	0.890	0.518	0.896
w. CNT (RF-L)	√		**88.4**	83.6	**90.3**	**70.1**	0.327	**0.886**	**0.514**	**0.884**

❖ CNT Implementation compared with ACE

Methods	ACE [42][5]		ACE w. RF-L		CNT		CNT w. RF-L	
	RMSE	relRMSE	RMSE	relRMSE	RMSE	relRMSE	RMSE	relRMSE
IIIT	0.477	0.169	0.323	0.133	0.300	0.128	**0.272**	**0.115**
SVT	0.963	0.361	0.890	0.326	0.455	0.165	**0.455**	**0.164**
IC03	0.555	0.206	0.509	0.192	0.372	0.147	**0.352**	**0.138**
IC13	0.518	0.193	0.502	0.188	0.275	0.107	**0.268**	**0.106**
IC15	0.889	0.364	0.896	0.361	0.614	0.261	**0.604**	**0.256**
SVTP	1.389	0.499	1.414	0.514	**0.724**	0.258	0.747	**0.256**
CT	1.001	0.443	1.200	0.442	0.854	0.420	**0.835**	**0.368**

❖ Generalization Ablation

Encoder	Decoder	w. CNT (RF-L)	IIIT	SVT	IC03	IC13	IC15	SVTP	CT	Avg.Gain
VGG	Bilstm-Attn		91.2	85.5	92.6	92.1	77.5	77.7	73.6	
VGG	Bilstm-Attn	√	91.8	86.9	92.9	92.9	78.0	78.9	74.7	+0.9
ResNet	Bilstm-Attn		93.7	89.0	92.3	93.2	79.3	81.2	80.6	
ResNet	Bilstm-Attn	√	94.1	88.4	94.5	94.5	81.9	82.0	82.6	+1.2
ResNet	CTC		91.7	85.8	91.5	91.7	74.1	73.2	76.7	
ResNet	CTC	√	92.1	86.9	92.1	92.4	76.5	75.8	78.9	+1.5
ResNet	Paral-Attn		90.0	82.8	87.6	89.0	72.4	71.0	73.3	
ResNet	Paral-Attn	√	90.3	85.8	92.2	93.0	73.8	75.8	77.8	+3.8

Experiment

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❋ Ablation Summary

❖ Optimization Ablation

Methods	Branch		Direction		Benchmark							Avg.
	RCG	CNT	C2R	R2C	IIIT	SVT	IC03	IC13	IC15	SVTP	CT	Acc
RCG	√				90.0	82.8	87.6	89.0	72.4	71.0	73.3	81.3
RCG w. CNT (JT-L)	√	√			89.6	83.9	92.6	91.7	72.6	74.0	78.1	82.4(+1.1)
RCG w. Fixed CNT (RF-L)	√	√	√		90.2	86.7	92.2	91.6	73.2	76.0	79.5	82.8(+1.5)
RCG w. CNT (Unidirectional RF-L)	√	√	√		90.7	86.6	92.6	91.2	73.2	76.0	80.2	82.9(+1.7)
RCG w. CNT (Bidirectional RF-L)	√	√	√	√	90.3	85.8	92.2	93.0	73.8	75.8	77.8	83.3(+2.0)
CNT		√			92.5	93.0	96.3	95.6	84.2	85.0	85.8	89.4
CNT w. RCG (JT-L)	√	√			93.0	94.3	96.2	96.1	84.9	86.4	83.7	89.8(+0.4)
CNT w. Fixed RCG (RF-L)	√	√		√	91.6	92.9	96.5	96.0	86.0	87.3	87.2	89.9(+0.5)
CNT w. RCG (Unidirectional RF-L)	√	√		√	92.6	93.5	96.6	95.2	86.0	86.7	89.6	90.0(+0.6)
CNT w. RCG (Bidirectional RF-L)	√	√	√	√	93.5	94.0	96.7	95.7	85.5	86.7	88.9	90.3(+0.9)

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Thank you