1. Retina Net (Retina)

Model Configuration:-

https://github.com/open-mmlab/mmdetection/blob/master/configs/retinanet_x101_32x4d_fpn_1x.py

Evaluation Table:-

Epoch	IOU			
	0.6	**0.7**	**0.8**	**0.9**
1	0.30836	0.287369	0.212812	0.070937
2	0.306977	0.292665	0.257603	0.147406
3	0.24834	0.239677	0.218308	0.125325
4	0.481253	0.465585	0.420817	0.297706
5	0.503137	0.489447	0.463206	0.36737
6	*0.170798*	*0.164214*	*0.149497*	*0.106894*
7	0.596206	0.577236	0.544715	0.45122
8	0.495803	0.477896	0.453274	0.351427
9	0.766404	0.741907	0.710411	0.598425
10	0.795247	0.767824	0.744059	0.647166
11	0.800735	0.77686	0.751148	0.653811
12	0.792384	0.768812	0.739801	0.645512
13	0.80367	0.776147	0.752294	0.655046
14	0.80663	0.779006	0.755064	0.655617
15	0.810711	0.781163	0.755309	0.655586
16	0.812963	0.781481	0.757407	0.655556
17	0.807728	0.776449	0.75253	0.655014
18	0.81146	0.780037	0.756007	0.658041
19	0.816744	0.785116	0.75907	0.662326
20	0.817505	0.785847	0.761639	0.664804
21	0.813716	0.780352	0.758109	0.656163
22	**0.818267**	**0.784716**	**0.762349**	**0.66356**

1. **Faster RCNN Hrnet (FRcnnHr)**

Model Configuration:-

https://github.com/open-mmlab/mmdetection/blob/master/configs/hrnet/faster_rcnn_hrnetv2p_w40_1x.py

Evaluation Table:-

EPOCH	IOU			
	0.6	**0.7**	**0.8**	**0.9**
1	0.420332	0.396872	0.338221	0.131965
2	0.604488	0.584853	0.537167	0.29453
3	0.649624	0.634586	0.57594	0.323308
4	0.693651	0.677778	0.650794	0.455556
5	0.782847	0.766423	0.740876	0.600365
6	0.774888	0.764126	0.728251	0.575785
7	0.775658	0.764759	0.730245	0.564941
8	0.846457	0.832677	0.814961	0.663386
9	0.884974	0.874611	0.864249	0.770984
10	0.881565	0.875386	0.858908	0.762101
11	0.89234	0.879917	0.867495	0.778468
12	0.888199	0.877847	0.861284	0.772257
13	**0.889119**	**0.876684**	**0.862176**	**0.781347**

3.Cascade RCNN X101 (CRcnnX)

Model Configuration:-

https://github.com/open-mmlab/mmdetection/blob/master/configs/cascade_rcnn_x101_64x4d_fpn_1x.py

Evaluation Table:-

EPOCH	IOU			
	0.6	**0.7**	**0.8**	**0.9**
1	0.420332	0.396872	0.338221	0.131965
2	0.604488	0.584853	0.537167	0.29453
3	0.649624	0.634586	0.57594	0.323308
4	0.693651	0.677778	0.650794	0.455556
5	0.782847	0.766423	0.740876	0.600365
6	0.774888	0.764126	0.728251	0.575785
7	0.775658	0.764759	0.730245	0.564941
8	0.846457	0.832677	0.814961	0.663386
9	0.884974	0.874611	0.864249	0.770984
10	0.881565	0.875386	0.858908	0.762101
11	0.926407	0.91342	0.900433	0.854978
12	0.922246	0.909287	0.898488	0.850972
13	0.927411	0.912243	0.901408	0.853738
14	0.926407	0.911255	0.900433	0.850649
15	0.928416	0.913232	0.902386	0.854664
16	0.928416	0.913232	0.902386	0.854664
17	**0.928571**	**0.91342**	**0.902597**	**0.852814**

4.Cascade RCNN Hrnet (CRccnHR)

Model Configuration:-

https://github.com/open-mmlab/mmdetection/blob/master/configs/hrnet/cascade_rcnn_hrnetv2p_w32_20e.py

Evaluation Table:-

EPOCH	IOU			
	0.6	**0.7**	**0.8**	**0.9**
1	0.543803	0.521739	0.462038	0.2427
2	0.639579	0.630549	0.606471	0.41836
3	0.672496	0.659777	0.63275	0.511924
4	0.772365	0.761736	0.735164	0.632418
5	0.757785	0.738754	0.723183	0.615917
6	0.826291	0.811268	0.773709	0.666667
7	0.820305	0.810152	0.79797	0.716751
8	0.800735	0.786042	0.764004	0.685032
9	0.794895	0.783956	0.763902	0.694622
10	0.879346	0.858896	0.850716	0.791411
11	0.894628	0.884298	0.865702	0.793388
12	**0.927039**	**0.909871**	**0.901288**	**0.832618**
13	0.915966	0.901261	0.884454	0.821429
14	0.883011	0.868769	0.852492	0.793489
15	0.918977	0.906183	0.886994	0.831557
16	0.851312	0.835763	0.816327	0.75413
17	0.904512	0.885624	0.873033	0.833158
18	0.911392	0.894515	0.881857	0.839662
19	0.917998	0.903088	0.888179	0.841321
20	0.918977	0.901919	0.886994	0.835821
21	0.917998	0.903088	0.886049	0.839191

5.Cascade Mask RCNN Deformable Convolution (CMRcnnDC)

Model Configuration:-

https://github.com/open-mmlab/mmdetection/blob/master/configs/dcn/cascade_mask_rcnn_dconv_c3-c5_r50_fpn_1x.py

Evaluation Table:-

EPOCH	IOU			
	0.6	**0.7**	**0.8**	**0.9**
1	0.654659	0.632733	0.598277	0.443226
2	0.771583	0.755396	0.732014	0.663669
3	0.794521	0.779909	0.767123	0.703196
4	0.713001	0.691742	0.68193	0.591987
5	0.857424	0.849558	0.829892	0.764995
6	0.832061	0.820611	0.801527	0.740458
7	0.861966	0.852036	0.82423	0.762661
8	0.857988	0.842209	0.822485	0.763314
9	**0.902287**	**0.885655**	**0.866944**	**0.839917**
10	0.90135	0.886812	0.86812	0.82243
11	0.902287	0.887734	0.871102	0.829522
12	0.907001	0.890282	0.873563	0.833856
13	0.907001	0.890282	0.873563	0.835946
14	0.908901	0.894241	0.875393	0.835602
15	0.909853	0.895178	0.878407	0.836478
16	0.908901	0.894241	0.879581	0.835602
17	0.910808	0.896118	0.881427	0.835257
18	0.910808	0.896118	0.879328	0.837356
19	0.909853	0.895178	0.878407	0.836478
20	0.909853	0.895178	0.878407	0.836478
21	0.90795	0.893305	0.876569	0.834728
22	0.910808	0.896118	0.879328	0.837356
23	0.908901	0.894241	0.877487	0.831414
24	0.910808	0.896118	0.879328	0.835257
25	0.908901	0.894241	0.877487	0.833508
26	0.909853	0.895178	0.878407	0.834382
27	**0.911765**	**0.897059**	**0.880252**	**0.834034**

6.Cascade Mask RCNN X101 (CMRcnnX)

Model Configuration:-

https://github.com/open-mmlab/mmdetection/blob/master/configs/cascade_mask_rcnn_x101_64x4d_fpn_1x.py

Evaluation Table:-

EPOCH	IOU			
	0.6	0.7	0.8	0.9
1	0.681423	0.662451	0.63083	0.531225
2	0.736842	0.723037	0.709232	0.543572
3	0.815311	0.798086	0.786603	0.725359
4	0.852295	0.846307	0.832335	0.740519
5	0.8583	0.846154	0.834008	0.791498
6	0.895769	0.887513	0.877193	0.819401
7	0.892147	0.885864	0.873298	0.839791
8	0.875127	0.864975	0.84264	0.8
9	0.931298	0.924755	0.909487	0.868048
10	0.927095	0.91839	0.905332	0.85963
11	0.928261	0.917391	0.904348	0.86087
12	0.929117	0.920393	0.907306	0.861505
13	0.932314	0.923581	0.908297	0.866812
14	0.931148	0.922404	0.90929	0.86776
15	0.929117	0.920393	0.907306	0.863686
16	0.931148	0.922404	0.90929	0.865574
17	0.930131	0.921397	0.908297	0.864629
18	0.930131	0.921397	0.908297	0.862445
19	0.931148	0.922404	0.90929	0.863388
20	0.931148	0.922404	0.90929	0.863388
21	0.931148	0.922404	0.90929	0.863388

7.Cascade Mask RCNN Hrnet (CMRcnnHR)

Model Configuration:-

https://github.com/open-mmlab/mmdetection/blob/master/configs/hrnet/cascade_mask_rcnn_hrnetv2p_w32_20e.py

Evaluation Table:-

EPOCH	IOU			
	0.6	**0.7**	**0.8**	**0.9**
1	0.723514	0.702842	0.666667	0.449612
2	0.756661	0.742451	0.728242	0.641208
3	0.776199	0.760213	0.735346	0.657194
4	0.8	0.788679	0.779245	0.709434
5	0.875252	0.861167	0.841046	0.78672
6	0.847107	0.836777	0.820248	0.764463
7	0.895337	0.880829	0.866321	0.831088
8	0.899044	0.886291	0.87779	0.835282
9	0.841176	0.827451	0.813725	0.770588
10	0.92735	0.918803	0.90812	0.867521
11	0.930586	0.915401	0.906725	0.867679
12	0.903564	0.890985	0.878407	0.84696
13	0.922092	0.909285	0.909285	0.881537
14	0.905263	0.901053	0.882105	0.84
15	0.936957	0.926087	0.908696	0.880435
16	0.922747	0.916309	0.905579	0.862661
17	0.938865	0.932314	0.917031	0.886463
18	0.937841	0.929117	0.920393	0.887677
19	0.938865	0.930131	0.919214	0.886463
20	0.939891	0.931148	0.920219	0.885246
21	**0.940919**	**0.932166**	**0.923414**	**0.886214**
22	0.940919	0.932166	0.923414	0.886214
23	0.940919	0.932166	0.923414	0.886214

ICDAR 19 Fine Tuned

Model Configuration:-

https://github.com/open-mmlab/mmdetection/blob/master/configs/hrnet/cascade_mask_rcnn_hrnetv2p_w32_20e.py

Epoch	Cascade_mask_rcnn_hrnet			
	0.6	**0.7**	**0.8**	**0.9**
1	0.940919	0.925602	0.916849	0.881838
2	0.938596	0.932018	0.923246	0.894737
3	0.943771	0.932745	0.92613	0.899669
4	0.936543	0.921225	0.910284	0.886214
5	0.940529	0.933921	0.92511	0.889868
6	0.937568	0.926616	0.917853	0.887185
7	0.940659	0.92967	0.923077	0.892308
8	0.938462	0.931868	0.923077	0.881319
9	0.938596	0.929825	0.916667	0.881579
10	0.937431	0.930845	0.922064	0.891328
11	0.939361	0.932745	0.923925	0.899669
12	0.940397	0.92936	0.922737	0.89404
13	**0.942605**	**0.931567**	**0.924945**	**0.900662**
14	0.941566	0.93054	0.923925	0.893054
15	0.940659	0.927473	0.923077	0.887912
16	0.940659	0.92967	0.923077	0.894505

TABLE BANK

without Annotation Correction and train dataset size 500

Dataset :- Word

	Word		
EPOCH	**Precision**	**Recall**	**F1**
1	0.6906908101	0.7279081729	0.7088112872
2	0.7399527014	0.7401142336	0.7400334587
3	0.7506459456	0.7959008635	0.7726112818
4	0.7278200208	0.7586095162	0.7428958859
5	0.7517135815	0.7864689868	0.768698633
6	0.758192104	0.7935960874	0.7754902255
7	0.7863115216	0.8096700549	0.7978198523
8	0.7995694352	0.8191094179	0.8092214875
9	0.7320646491	0.7577066205	0.7446649598
10	0.7691164702	0.7938158906	0.7812710148
11	**0.8028016151**	**0.827380258**	**0.8149056475**
12	0.7835828758	0.8086614805	0.7959246782
13	0.7849088146	0.8124940672	0.7984632586
14	0.7925270256	0.8190752622	0.8055824768
15	0.7931177911	0.8168240051	0.8047963624
16	0.7915702685	0.8169328196	0.8040515882
17	0.7916470971	0.8173407971	0.8042887976

Dataset :- Latex

	Latex		
EPOCH	**Precision**	**Recall**	**F1**
1	0.9228870792	0.9492738634	0.9358945197
2	0.9266636538	0.9374905902	0.9320456807
3	0.9193349624	0.9433708627	0.9311978359
4	0.9172263581	0.9550716259	0.9357665037
5	0.9237093877	0.9464826676	0.9349573728
6	0.9221231843	0.9490151556	0.9353759245
7	0.9231681782	0.9498620223	0.936324884
8	0.9189220887	0.9506428531	0.934513369
9	0.9201000243	0.9524291395	0.9359855017
10	**0.9305578405**	**0.9527632518**	**0.941529639**
11	0.9142672362	0.9520920272	0.9327963414
12	0.9200840963	0.955957574	0.9376778507
13	0.9230835176	0.9520331336	0.9373348515
14	0.9220339628	0.9525904131	0.9370631523

Dataset :- Both

	Both		
EPOCH	**Precision**	**Recall**	**F1**
1	0.7648168564	0.7495721225	0.7571177582
2	0.8003890801	0.8322070608	0.8159880171
3	0.8194695269	0.8361888072	0.8277447492
4	0.8323342345	0.8726059985	0.8519944943
5	0.8156213844	0.8502366859	0.8325693949
6	0.8261896477	0.8499982769	0.837924873
7	0.7911923604	0.8284949308	0.809414093
8	0.8402422099	0.8626743464	0.8513105314
9	0.841536747	0.8688842972	0.8549918951
10	0.8414817273	0.8794623093	0.8600529098
11	0.8536566686	0.8780566237	0.8656847477
12	**0.8510621144**	**0.8815610046**	**0.8660431277**
13	0.8505321905	0.8803833177	0.8652003499

TABLE BANK
with Annotation Correction and train dataset size 1500

Dataset :- Word

	Word		
EPOCH	Precision	Recall	F1
1	0.9663132339	0.9701914249	0.968248446
2	0.979575863	0.9845980611	0.9820805414
3	0.9854824096	0.9898770928	0.9876748627
4	0.9843642852	0.9944516226	0.989382243
5	0.986142864	0.9886099919	0.9873748868
6	0.9842226762	0.9906534684	0.987427602
7	0.9846453231	0.9945141101	0.989555112
8	0.9868242867	0.9903130233	0.988565577
9	0.9862395302	0.9909892989	0.9886087095
10	**0.9880134322**	**0.9930677228**	**0.99053413**
11	0.9861041274	0.9922218079	0.9891535086
12	0.9850163229	0.9914184234	0.9882070042
13	0.9801580823	0.9945153147	0.987284505
14	0.9874671496	0.9924378042	0.9899462373
15	0.9872649755	0.9932359384	0.9902414561
16	0.9852801549	0.9938701234	0.9895564979
17	0.9851871432	0.9939585539	0.9895534115
18	0.9857689236	0.9940340942	0.9898842564
19	0.9867220296	0.9938970597	0.9902965484
20	0.9862173301	0.9937903814	0.9899893732
21	0.9862339405	0.9940363467	0.9901197726

Dataset :- Latex

	Latex		
EPOCH	**Precision**	**Recall**	**F1**
1	0.8464658325	0.8852926763	0.8654439963
2	0.9218571268	0.9467914143	0.9341579154
3	0.9289714538	0.9270370133	0.9280032254
4	0.9089079786	0.9287697614	0.918731536
5	0.9457037387	0.9439637668	0.9448329517
6	0.9384518818	0.9456510854	0.9420377295
7	0.9461505847	0.9517564423	0.9489452345
8	0.9429540684	0.9534258001	0.948161022
9	0.9446579774	0.9630394992	0.9537601812
10	0.9018629357	0.9111222727	0.9064689594
11	0.947573742	0.9593630904	0.9534319733
12	0.9315259066	0.9485390059	0.9399554787
13	0.9384698852	0.9425383212	0.9404997034
14	**0.9592066966**	**0.97280196**	**0.9659564943**
15	0.9509428235	0.959083229	0.9549956793
16	0.9398396232	0.9514829693	0.9456254569
17	0.9423361839	0.9564856434	0.9493581948

Dataset :- Both

	Both		
EPOCH	**Precision**	**Recall**	**F1**
1	0.8853102504	0.9120978982	0.8985044597
2	0.8761654193	0.8827260655	0.8794335068
3	0.9541299304	0.9449597206	0.9495226852
4	0.9304259486	0.9182692602	0.9243076343
5	0.9307271016	0.9373854537	0.9340444118
6	0.9550765435	0.9648758474	0.959951188
7	0.9513886186	0.9546137883	0.9529984748
8	0.9527138997	0.9615421895	0.9571076871
9	0.9589037691	0.9741595846	0.9664714771
10	0.9570692938	0.9656109653	0.961321156
11	**0.9570524116**	**0.9731934606**	**0.965055449**
12	0.9555990994	0.9668770365	0.9612049877
13	0.9598927772	0.9682749661	0.964065652
14	0.9547643202	0.9620421454	0.9583894164
15	0.9574011207	0.971713968	0.9645044481
16	0.9570564339	0.9602325118	0.9586418422
17	0.9589442461	0.9675446361	0.9632252438
18	0.9600900279	0.9709406212	0.9654848394

Baseline Model (Resnext101)
ICDAR_Test are Original Testing
ICDAR_Dilated are Dilated Testing set
ICDAR_Smudge are Smudge Testing set

Baseline Trained and Tested on ICDAR_Test

EPOCH	Trained and Tested on ORIGNAL			
	0.6	**0.7**	**0.8**	**0.9**
1	0.328619	0.27787	0.157238	0.027454
2	0.20246	0.165044	0.105074	0.018452
3	0.489423	0.464265	0.40709	0.124643
4	0.52844	0.512538	0.43792	0.064832
5	0.568449	0.550196	0.509778	0.290743
6	0.723297	0.70984	0.66947	0.491169
7	0.761989	0.74778	0.690941	0.509769
8	0.688189	0.664567	0.604724	0.251969
9	0.811268	0.794366	0.762441	0.597183
10	0.816714	0.801519	0.767331	0.605888
11	0.840353	0.818805	0.787463	0.607248
12	0.831395	0.817829	0.782946	0.625969
13	0.832527	0.815102	0.78606	0.635044
14	0.835763	0.816327	0.787172	0.633625
15	0.831721	0.812379	0.779497	0.618956
16	0.831721	0.812379	0.783366	0.628627
17	**0.835763**	**0.81827**	**0.787172**	**0.621963**

Baseline Trained on Dilated
And Tested On ICDAR_Dilated and ICDAR_Test

EPOCH	Trained on dilate+original and Tested on dilate +Original							
	0.6		0.7		0.8		0.9	
	ICDAR_ Test	ICDAR_ Dilated	ICDAR_ Test	ICDAR_ Dilated	ICDAR_ Test	ICDAR_ Dilated	ICDAR_ Test	ICDAR_ Dilated
1	0.441572	-	0.412616	-	0.315408	-	0.087901	-
2	0.458558	-	0.441335	-	0.399354	-	0.184069	-
3	0.522489	-	0.504005	-	0.45841	-	0.264941	-
4	0.655564	-	0.632854	-	0.604088	-	0.417865	-
5	0.730213	-	0.713191	-	0.675745	-	0.514043	-
6	0.761313	-	0.741792	-	0.700976	-	0.505768	-
7	0.791859	-	0.780759	-	0.754857	-	0.599445	-
8	0.819231	-	0.8	-	0.759615	-	0.426923	-
9	0.855721	-	0.843781	-	0.8199	-	0.680597	-
10	0.853175	0.84705 9	0.837302	0.831373	0.821429	0.8	0.706349	0.662745
11	0.867543	0.86002	0.853387	0.843907	0.833165	0.817724	0.695652	0.674723
12	0.868421	0.86086 1	0.854251	0.840841	0.836032	0.808809	0.698381	0.680681
13	0.866667	0.85828 3	0.852525	0.840319	0.832323	0.810379	0.694949	0.678643
14	0.869565	0.86113 9	0.851365	0.843157	0.833165	0.813187	0.697674	0.681319
15	0.873984	0.85914 1	0.857724	0.843157	0.839431	0.809191	0.703252	0.677323
16	0.869036	0.85657 4	0.854822	0.840637	0.838579	0.808765	0.702538	0.693227

Baseline Trained On SMUDGED Dataset
Tested On ICDAR_Test and ICDAR_ SMUDGE

EPOCH	Trained on Smudge+original and Tested on Smudge + Original							
	0.6		0.7		0.8		0.9	
	ICDAR_ Test	ICDAR_ SMUDG E	ICDAR_ Test	ICDAR_ SMUDG E	ICDAR_ Test	ICDAR_ SMUDG E	ICDAR_ Test	ICDAR_ SMUDG E
1	0.410501	-	0.381862	-	0.292124	-	0.071599	-
2	0.479247	-	0.456004	-	0.405091	-	0.185944	-
3	0.529519	-	0.514912	-	0.457699	-	0.265368	-
4	0.650038	-	0.618292	-	0.551776	-	0.226757	-
5	0.691438	-	0.673667	-	0.638126	-	0.423263	-
6	0.667704	-	0.655253	-	0.628794	-	0.362646	-
7	0.708197	-	0.696721	-	0.670492	-	0.467213	-
8	0.790698	-	0.772093	-	0.723721	-	0.55814	-
9	0.846686	-	0.840752	-	0.820969	-	0.658754	-
10	0.852036	-	0.840119	-	0.818272	-	0.649454	-
11	0.847761	0.849452	0.839801	0.829511	0.823881	0.801595	0.662687	0.656032
12	0.854291	0.844091	0.844311	0.826216	0.828343	0.804369	0.674651	0.647468
13	0.857715	0.847525	0.847695	0.825743	0.831663	0.805941	0.673347	0.653465
14	0.85657	0.845771	0.84654	0.827861	0.830491	0.80597	0.674022	0.652736
15	0.858576	0.848907	0.848546	0.827038	0.832497	0.809145	0.678034	0.652087
16	0.859438	0.846077	0.849398	0.82423	0.833333	0.806356	0.690763	0.647468
17	**0.86318**	**0.84158**	**0.85311**	**0.82178**	**0.83903**	**0.80396**	**0.68410**	**0.65346**

Baseline Trained on All
And Tested on ICDAR_Test

Epoch	Trained On ALL and Test On Original			
	0.6	**0.7**	**0.8**	**0.9**
1				
2	0.471302	0.439294	0.290287	0.020971
3	0.755989	0.734694	0.670807	0.362023
4	0.617037	0.604152	0.555476	0.287759
5	0.736301	0.729452	0.683219	0.489726
6	0.800371	0.789229	0.761374	0.499536
7	0.773381	0.764388	0.739209	0.580935
8	0.782214	0.76225	0.724138	0.577132
9	0.864919	0.84879	0.824597	0.566532
10	0.879753	0.869476	0.850976	0.723535
1	**0.887734**	**0.883576**	**0.862786**	**0.735967**

Baseline Trained On All Dataset And Tested On ICDAR_ Dilated

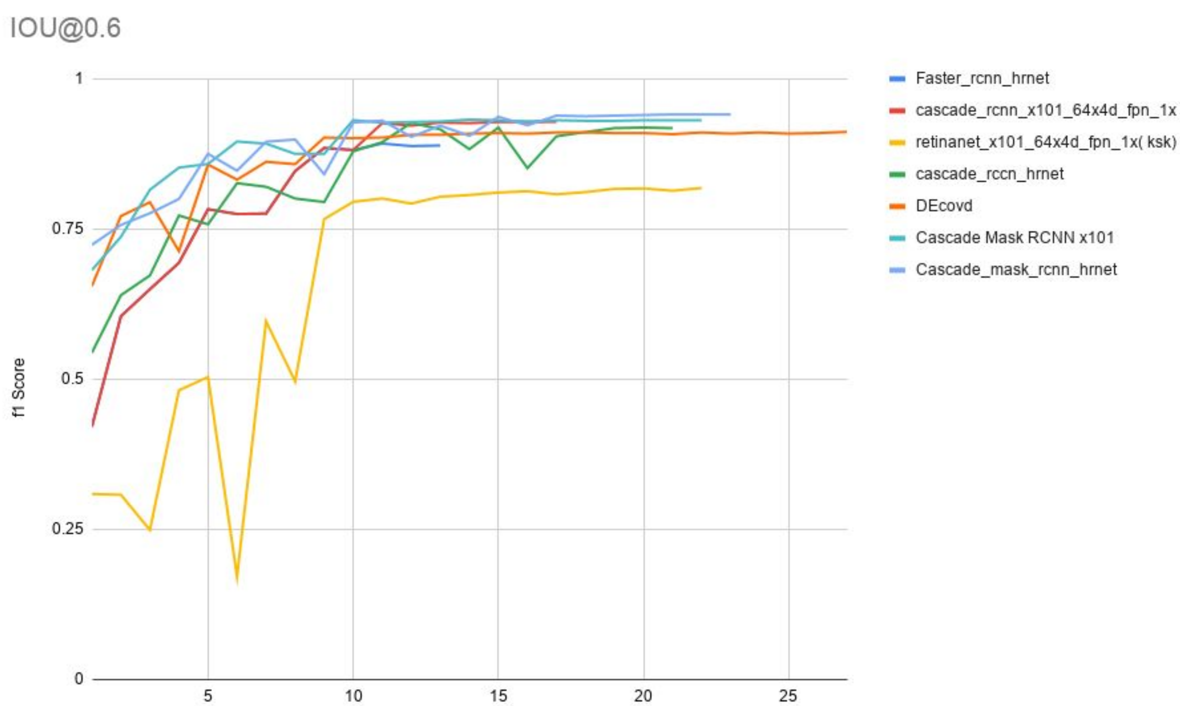
EPOCH	Trained On ALL TESTED ON DILATED			
	0.6	**0.7**	**0.8**	**0.9**
1	0.483191	0.438746	0.274644	0.020513
2	0.745645	0.721254	0.651568	0.367596
3	0.608511	0.598582	0.55461	0.307801
4	0.726655	0.704584	0.677419	0.47708
5	0.795937	0.781163	0.755309	0.526316
6	0.781818	0.769091	0.734545	0.543636
7	0.783809	0.765409	0.724931	0.572217
8	0.838454	0.824579	0.794846	0.539148
9	0.876684	0.860104	0.841451	0.702591
10	**0.88377**	**0.86911**	**0.846073**	**0.72251**

Table Structure Recognition Results
(ICDAR'19)

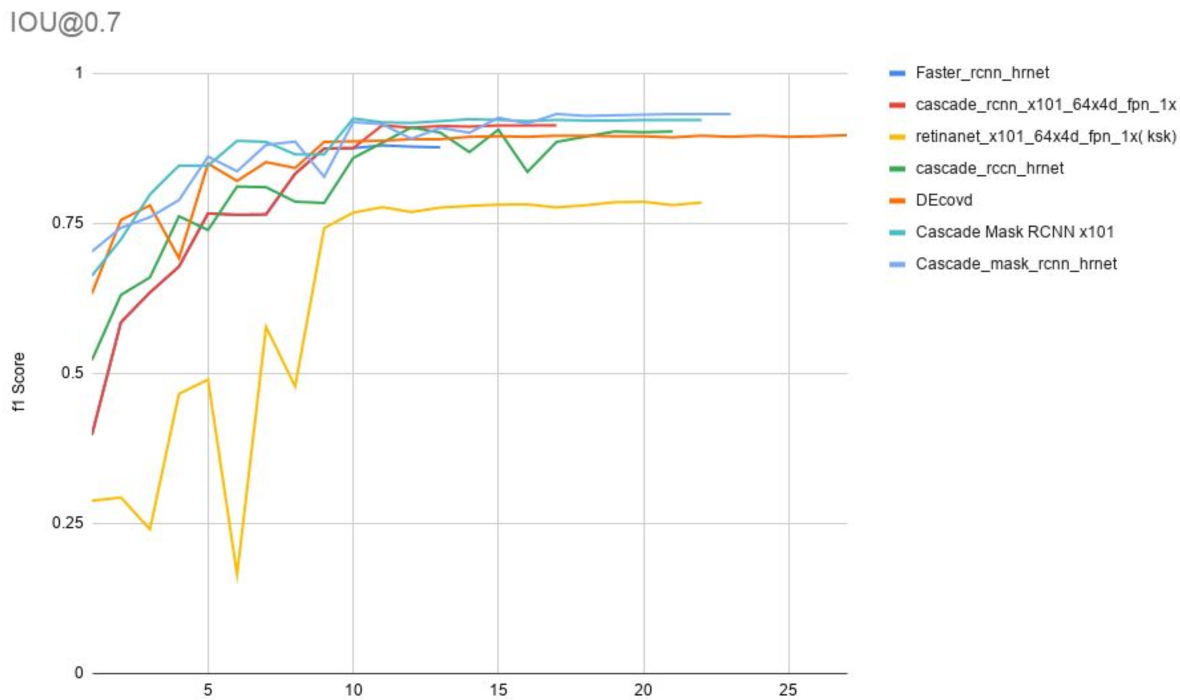
Team Name	IoU@0.6			IoU@0.7			IoU@0.8			IoU@0.9			WAvg. F1
	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1	
Ours	0.4988	0.39	0.4377	0.403	0.3151	0.3537	0.2164	0.1692	0.1899	0.041	0.03208	0.036	0.2315
NLPR-PAL	0.3224	0.4206	0.365	0.269	0.3509	0.3046	0.1722	0.2246	0.195	0.0305	0.0397	0.0345	0.2064
HCL IDORAN	0.4206	0.001	0.0013	0.0012	0.0007	0.0009	0.0003	0.0002	0.0002	0.0001	8.00E-05	9.00E-05	3.00E-04

Models and their Performance Graph for each IoU value

1) IoU 0.6

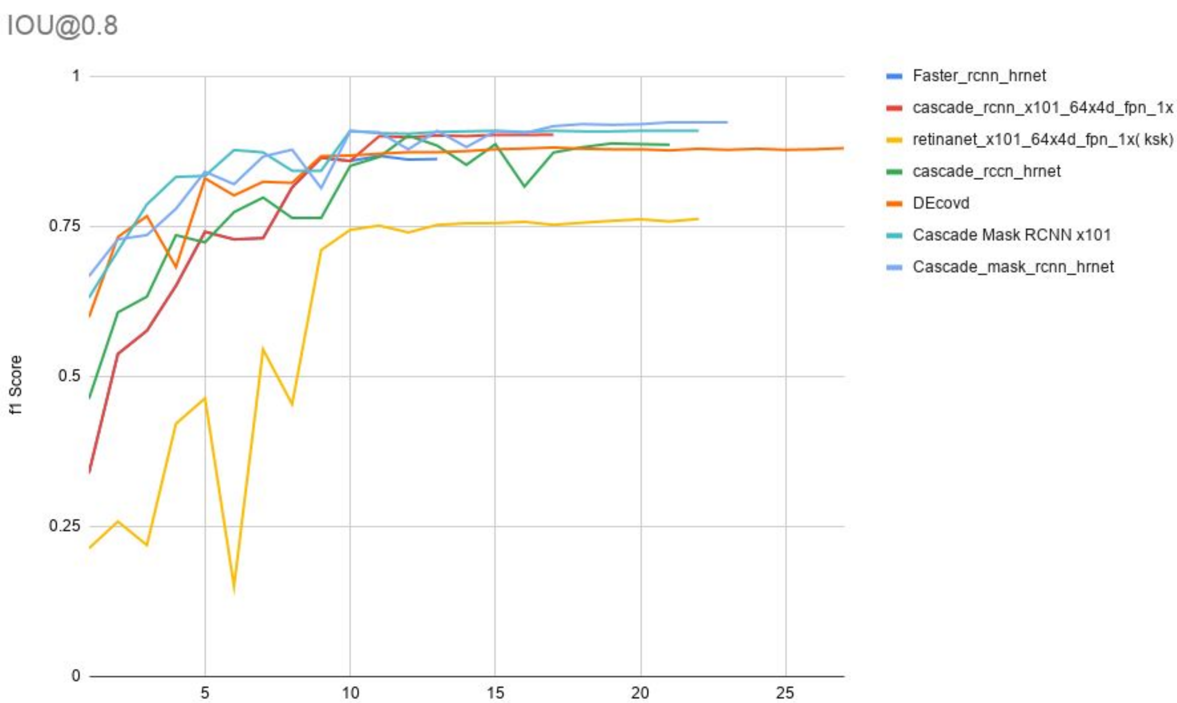


2) IoU 0.7



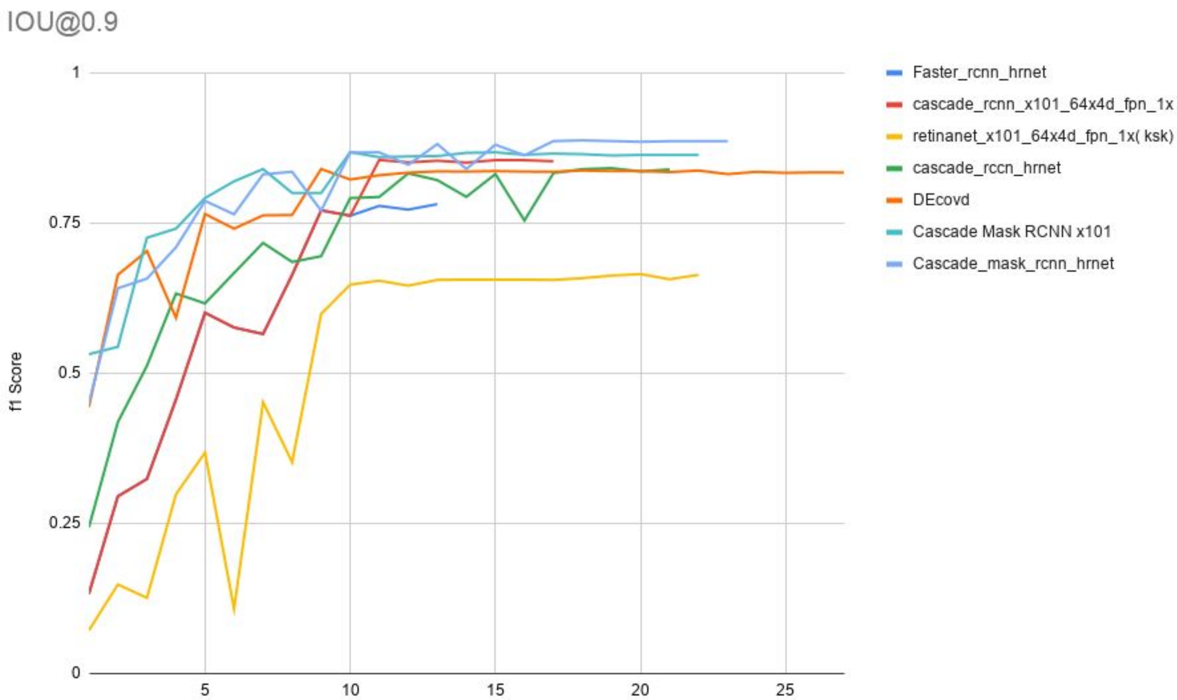
IOU@0.7
1
0.75
0.5
0.25
0
f1 Score
5
10
15
20
25
Faster_rcnn_hrnet
cascade_rcnn_x101_64x4d_fpn_1x
retinanet_x101_64x4d_fpn_1x(ksk)
cascade_rccn_hrnet
DEcovd
Cascade Mask RCNN x101
Cascade_mask_rcnn_hrnet

3) IoU 0.8



IOU@0.8
1
0.75
0.5
0.25
0
f1 Score
5
10
15
20
25
Faster_rcnn_hrnet
cascade_rcnn_x101_64x4d_fpn_1x
retinanet_x101_64x4d_fpn_1x(ksk)
cascade_rccn_hrnet
DEcovd
Cascade Mask RCNN x101
Cascade_mask_rcnn_hrnet

4) IoU 0.9



IOU@0.9
f1 Score
1
0.75
0.5
0.25
0
5
10
15
20
25
Faster_rcnn_hrnet
cascade_rcnn_x101_64x4d_fpn_1x
retinanet_x101_64x4d_fpn_1x(ksk)
cascade_rccn_hrnet
DEcovd
Cascade Mask RCNN x101
Cascade_mask_rcnn_hrnet

Dataset link, Preparation And results

Links

1. **Marmot Dataset**

   http://www.icst.pku.edu.cn/cpdp/sjzy/index.htm

2. **ICDAR'19 Dataset and Evaluation Tool**

   https://github.com/cndplab-founder/ICDAR2019_cTDaR

   https://github.com/cndplab-founder/ctdar_measurement_tool

3. **Github Dataset**

   https://github.com/sgrpanchal31/table-detection-dataset

4. **Tablebank Dataset**

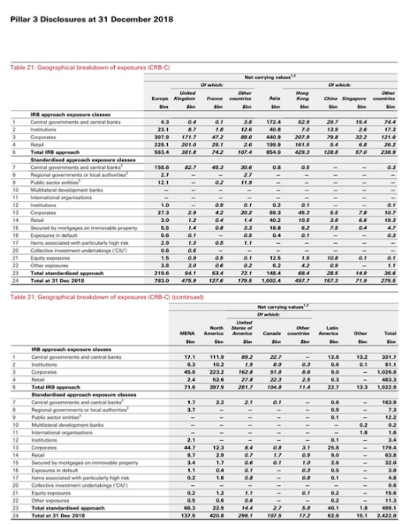
   https://github.com/doc-analysis/TableBank

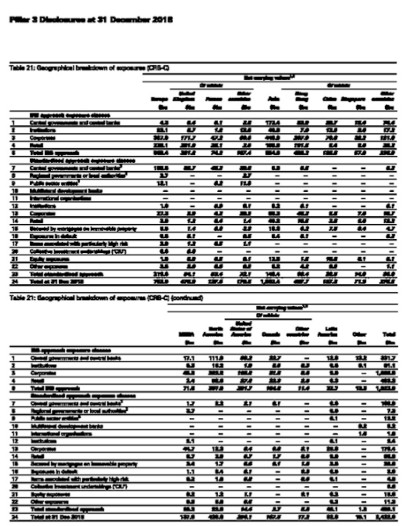
Preparation:

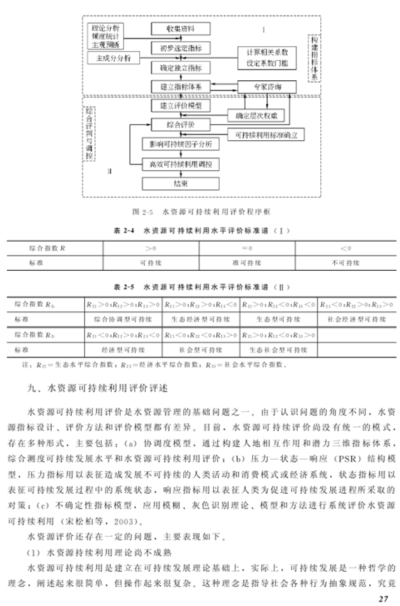
Original

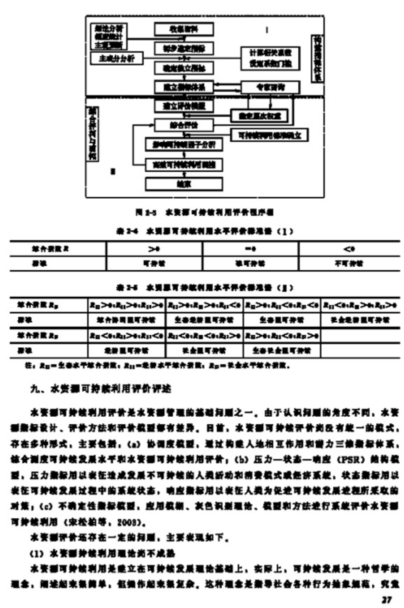
Dilation

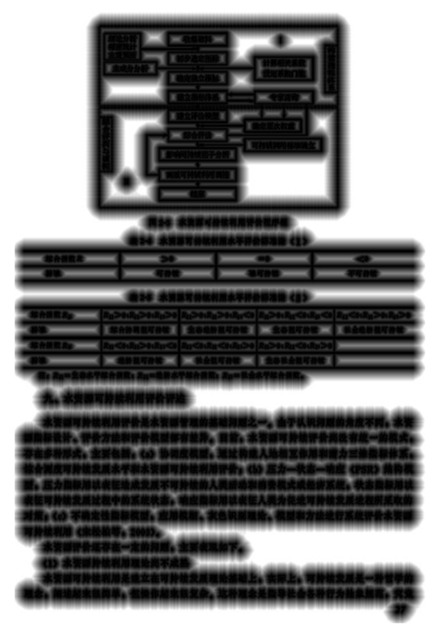
Smudge











2.1 Results

Location-Aware User Modelling System. Logbook data shows the most commo location of Pocket PC use to be at home, followed by various rooms in EECE. Som students also used their Pocket PC in other parts of the campus and elsewhere. Result of 3 typical users are presented in Table 1, as an example of similarities an differences between Pocket PC use. 10 of the generally common activities are listed reading, email, web browsing, notes, calendar, computer assisted learning, wor processing, calculator, music, games. Each user also performed a few additional task in other categories, not shown (e.g. MSN Messenger, Excel, viewing lecture slides).

Table 1: Activities and location of use of Pocket PC by 3 students

	Location	*read*	*mail*	*web*	*note*	*cal*	*CAL*	*WP*	*calc*	*mus*	*gam*
S1	home	1	2		5	4	2	2	1	7	1
	EECE G16	1	2	1	4	1			1		
	EECE 337		1	1		1			1	2	
	EECE 421	1		1						1	
	EECE 435			2					2		
	EECE CR	1	3	3							
	EECE lib		3	1		1				1	
	main lib			3	1		1				
	shop				4			1			
S2	home	1	4	3	1	4	2	2		7	3
	other home		1			1		1		1	
	EECE 123		1	1							
	EECE 337		5							1	
	EECE 522				1	1					
	EECE CR		1								
	EECE lib							1			
	EECE rec	1	2								
	campus		1			1					
	restaurant		1			1				1	
	train		3							1	1
S3	home	1	1		20	4	2			4	8
	EECE 225		1	2							
	EECE 337			2							
	EECE 421	1	1	1	9					1	1
	learn centre			1	1						

2.1 Results

Location-Aware User Modelling System. Logbook data shows the most common location of Pocket PC use to be at home, followed by various rooms in EECE. Some students also used their Pocket PC in other parts of the campus and elsewhere. Results of 3 typical users are presented in Table 1, as an example of similarities and differences between Pocket PC use. 10 of the generally common activities are listed: reading, email, web browsing, notes, calendar, computer assisted learning, word processing, calculator, music, games. Each user also performed a few additional tasks in other categories, not shown (e.g. MSN Messenger, Excel, viewing lecture slides).

Table 1: Activities and location of use of Pocket PC by 3 students

Result:-

bordered|1.00

债权单位名称	金额	占比%	款项性质	是否关联方
江苏省糖烟酒总公司	12,251.20	26.09	预收研发园购房款	否
南京凯盛开能环保能源有限公司	10,700.00	22.79	预收研发园购房款	否
南京凯盛自控工程有限公司	5,300.00	11.29	预收研发园购房款	否
南京公用发展股份有限公司	4,663.20	9.93	预收研发园购房款	否
南京路灯工程建设有限责任公司	3,595.20	7.66	预收研发园购房款	否
合计	36,509.60	77.76		

图表 6-29：截至 2018 年 9 月末发行人预收款项账龄结构情况

单位：万元

bordered|1.00

账龄	金额	比例%
1 年以内	4,327.04	9.21
1-2 年	9,588.56	20.42
2-3 年	14,930.80	31.80
3 年以上	18,111.10	38.57
合　　计	46,361.87	100

（5）其他应付款：

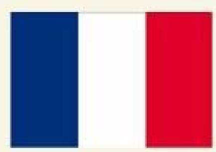
近三年又一期末,发行人其他应付款余额为 69,377.45 万元、44,690.56 万元、29,707.04 和 99,165.11 万元，占负债总额的比例为 3.73%、2.41%、1.75%和 5.12%，均为与非关联企业的往来款。

根据新的财务报表要求，其他应付款中包含应付利息。2018 年 9 月末，发行人其他应付款余额为 99,165.11 万元，其中应付利息为 8,746 万元，其他应付款实际较年初增加 60,712.07 万元，主要是新增非关联企业的往来款。

Table 2.1. Top 20 countries in online service delivery

Country	Online Service Index
France	1.0000
Singapore	0.9921
Republic of Korea	0.9764
Japan	0.9449
Spain	0.9449
United States	0.9449
Bahrain	0.9370
Australia	0.9291
Netherlands	0.9291
Canada	0.9134
United Kingdom	0.8976
United Arab Emirates	0.8819
Israel	0.8740
Uruguay	0.8504
New Zealand	0.8425
Chile	0.8189
Colombia	0.7874
Estonia	0.7717
Finland	0.7717
Saudi Arabia	0.7717

Box 2.1. France public service—commitment to continuous improvement



Taking the top place in the 2014 Online Service Index, France scores well across all practice areas and stages of online service development due to ongoing action to improve the quality of public services, integrate governmental websites and encourage consultation with citizens on both public policy and service delivery methods. The official website of the national administration (service-public.fr) directs individuals, businesses and associations to relevant services by event as well as by subject, invites ideas about administrative simplification, connects citizens with current debates and consultations and facilitates interaction with government through single sign-on.

A leader in the field, France has also committed to further expanding online public service delivery while containing costs by reviewing free alternatives to commercial ICT infrastructure and applications in a systematic fashion and expanding the use of open source software. The new policy, introduced in 2012, aims to lower ICT expenditures and improve agility while encouraging innovation and engagement of other actors, such as local authorities and developer communities, in e-service co-production.[1]

Source: http://circulaire.legifrance.gouv.fr/pdf/2012/09/cir_35837.pdf. Accessed 29 October 2013.

Table 6. Average time in seconds used for B&B Stage1 and for GP Stage. The time spend in each stage increases in proportion to the size of the training set.

	GP-35		GP-15		GP-5	
Problem	B&B Stage1	GP Stage	B&B Stage1	GP Stage	B&B Stage1	GP Stage
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	5.78	[illegible]	[illegible]	[illegible]	1.52
[illegible]	[illegible]	4.98	[illegible]	[illegible]	[illegible]	[illegible]
gesa2	[illegible]	5.89	[illegible]	[illegible]	[illegible]	1.62
gt2	[illegible]	5.58	[illegible]	[illegible]	[illegible]	1.70
[illegible]	[illegible]	6.19	[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	6.08	[illegible]	[illegible]	[illegible]	[illegible]
p2756	[illegible]	5.69	[illegible]	2.65	[illegible]	1.46
pk1	[illegible]	5.71	[illegible]	2.85	[illegible]	1.52
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	5.02	[illegible]
[illegible]	[illegible]	6.06	[illegible]	[illegible]	1.51	1.65
[illegible]	[illegible]	5.40	[illegible]	[illegible]	[illegible]	1.18
vpm2	1.98	5.17	0.97	2.39	0.38	1.31

Table 5 depicts the best and worst solutions obtained by each GP setup and Table 6 shows how the size of the training set affects the time spent in B&B Stage1 and in GP Stage. It is worth mentioning that GP-35, supported by a larger training set, manages to do best despite the significantly less time spent in B&B Stage2[6], in comparison to all other methods.

7 Conclusions and Further Research

We used Genetic Programming as a component in a Branch and Bound framework, where GP is utilized for generating the node selection heuristic for MIP. We believe that the experimental results obtained by our prototype implementation show that the hybrid B&B-GP approach we introduce portrays significant potential: supported by a properly constructed training set of adequate size, problem-instance specific heuristics can be evolved, capable of consistently guiding B&B towards promising areas of the search space.

Concerning our future research efforts, these will be directed in two fronts: The first one is to incorporate multiple GP Stages in our design, as well as to experiment with more elaborate GP structures and techniques like ADFs and Interval Arithmetic. The second one will be to increase our understanding of how the training set construction method adopted in the GP Stage affects the search in B&B Stage2. In addition to the above, we would like to apply our approach to more domains where B&B heuristic-based search is used.

References

1. Michalewicz, Z., Fogel, D.B.: How to Solve it: Modern Heuristics. Springer-Verlag (2002)

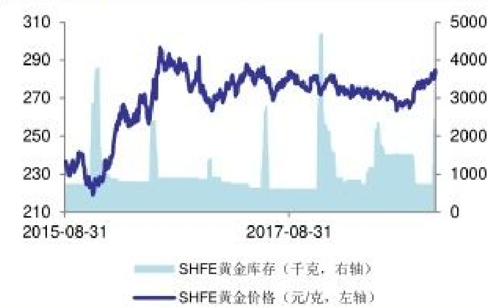
[6] The duration of B&B Stage2 equals the total run time minus the duration of B&B Stage1 and of GP Stage.

表7：贵金属价格及涨跌幅（元/克，元/千克，美元/盎司）

贵金属品种	现价	本周涨跌幅（%）	本月涨跌幅（%）	年初至今涨跌幅（%）
SHFE 黄金	284.8	1.50	2.24	2.48
SHFE 白银	3,591	0.31	2.10	-7.47
COMEX 黄金	1,259.1	1.43	2.33	-2.94
COMEX 白银	14.7	0.40	2.03	-13.1?
美元指数	96.95	-0.50	-0.25	5.09

资料来源：wind，中国银河证券研究院

图 21：SHFE 黄金价格及库存



资料来源：Wind，中国银河证券研究院

图 22：COMEX 黄金价格及库存

资料来源：Wind，中国银河证券研究院

图 23：SHEF 白银价格及库存

资料来源：Wind，中国银河证券研究院

图 24：COMEX 白银价格及库存

资料来源：Wind，中国银河证券研究院

relatively high level in 2011, while our pre-sales encountered tightened real estate regulations, and (ii) four projects were located in county-level towns of Zhejiang and Jiangsu provinces, which were mostly affected by tightening regulations. From 2013 to 2014, we adjusted our land acquisition strategy by shifting our investment focus to key cities in Zhejiang Province, such as Hangzhou and Wenzhou, and recognized increasing gross profit margin from 2016 onward.

Other Income and Other Gains – Net

Our other income primarily consists of income from the management and consulting services that we provided to the Group's joint ventures and associates in relation to property development projects. The management and consulting services provided by us mainly include project procurement, cost management, product development, human resources management, planned operations management, financial management and other services. Our clients are mainly our Group's joint ventures and associates, such as Zhejiang Dexin Dongcheng Property Co., Ltd.* (浙江德信東城置業有限公司), Hangzhou Binrun Real Estate Development Co., Ltd.* (杭州濱潤房地產開發有限公司), Zhejiang Jinao Real Estate Co., Ltd.* (浙江金澳置業有限公司), and Zhejiang Hongning Real Estate Co., Ltd.* (浙江鴻寧置業有限公司). The relevant income is determined based on the type of services we provided to our clients and mutual agreement of both parties, and in general with reference to certain proportion of the total contracted sales of the relevant property development projects.

Our other gains – net primarily include realised and unrealised gains on financial assets at fair value through profit or loss and gains on disposal of subsidiaries.

The following tables set forth our other income and other net gains for the periods indicated.

Other Income

	Year ended December 31,			Nine months ended September 30,	
	2015	2016	2017	2017	2018
	RMB'000	RMB'000	RMB'000	RMB'000 (Unaudited)	RMB'000
Management and consulting service income	20,881	66,618	60,328	34,781	15,387
Others	3,207	2,886	2,212	1,056	2,500
Total	24,088	69,504	62,540	35,837	17,887

Other Gains – Net

	Year ended December 31,			Nine months ended September 30,	
	2015	2016	2017	2017	2018
	RMB'000	RMB'000	RMB'000	RMB'000 (Unaudited)	RMB'000
Gains on financial assets at fair value through profit or loss	2,076	5,506	20,520	13,800	6,328
Gains on disposal of subsidiaries	6,159(1)	–	–	–	30,018(2)
Exchange gain	–	–	–	–	10,488
Others	285	1,401	314	1,189	4,212
Total	8,520	6,907	20,834	14,989	51,046