

Table Extraction

What Is Table Extraction?

- Table region detection
 - Identify all tables
 - Separate tables from non-table text
 - Separate tables from each other
- Cell structure recognition
 - Partition text into cells
 - Define rows and columns
 - Find cell span and cell-to-cell overlap (along X- or Y-axis)

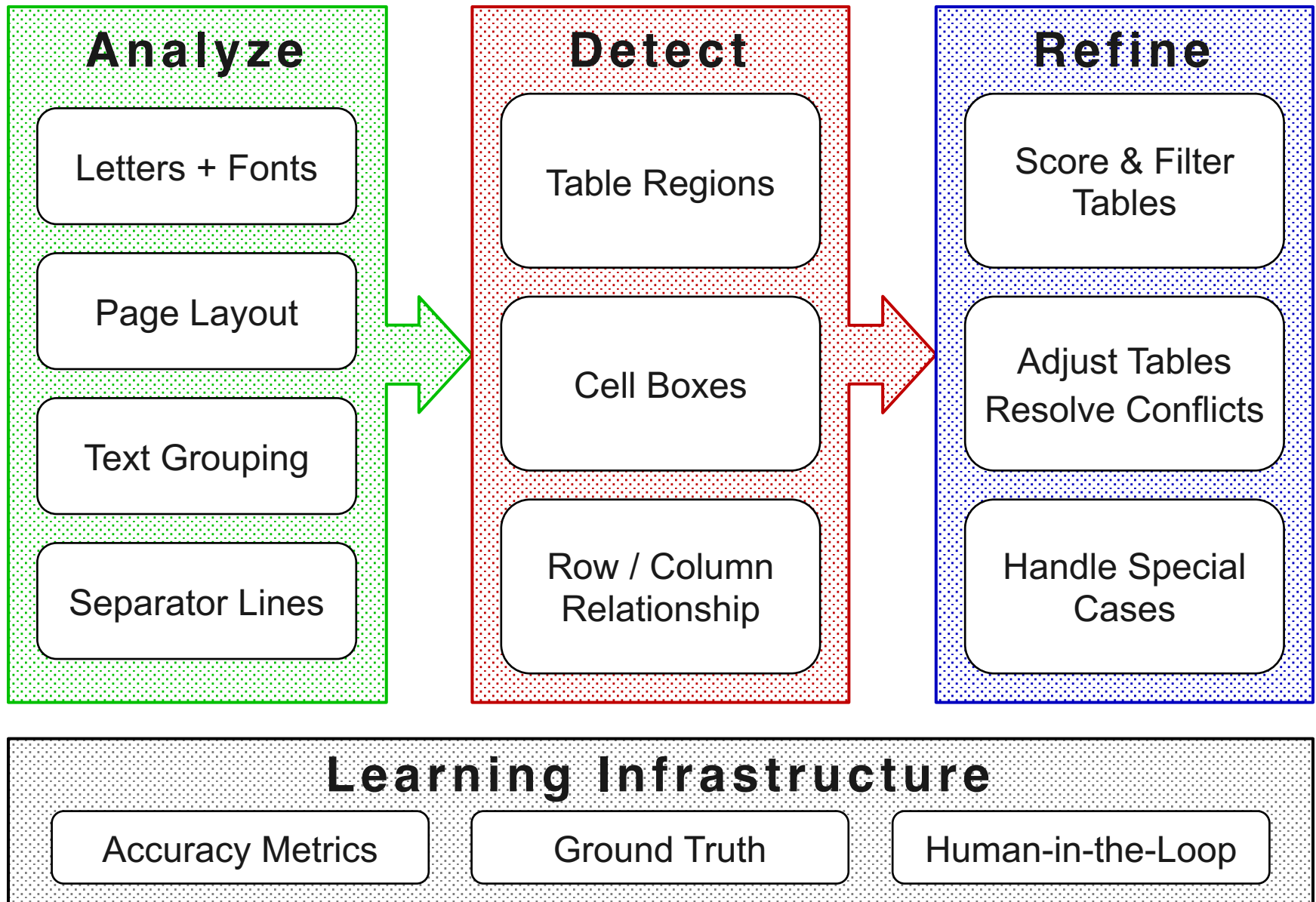
Table Extraction Timeline

- **Early 1990s : Separator based “top-down” methods**
 - Ruled line tables
 - Extend to white-space “lines”
- **1990s – early 2000s : “Bottom-up” text clustering**
 - Group text into columns (or rows), then to tables
 - Use space features (gaps, overlap, alignment) and keywords
- **2000s – early 2010s : Machine Learning (supervised or not)**
 - Classify text-rows using CRF, SVM, HMM, etc.
 - Probabilistic models for tables
 - Graph-based models for cell structure
- **Late 2010s : Deep Learning**
 - Scanned image table detection with R-CNN, YOLO, RetinaNet
 - Graph neural networks for cell structure
 - Natural language embeddings for text linkage

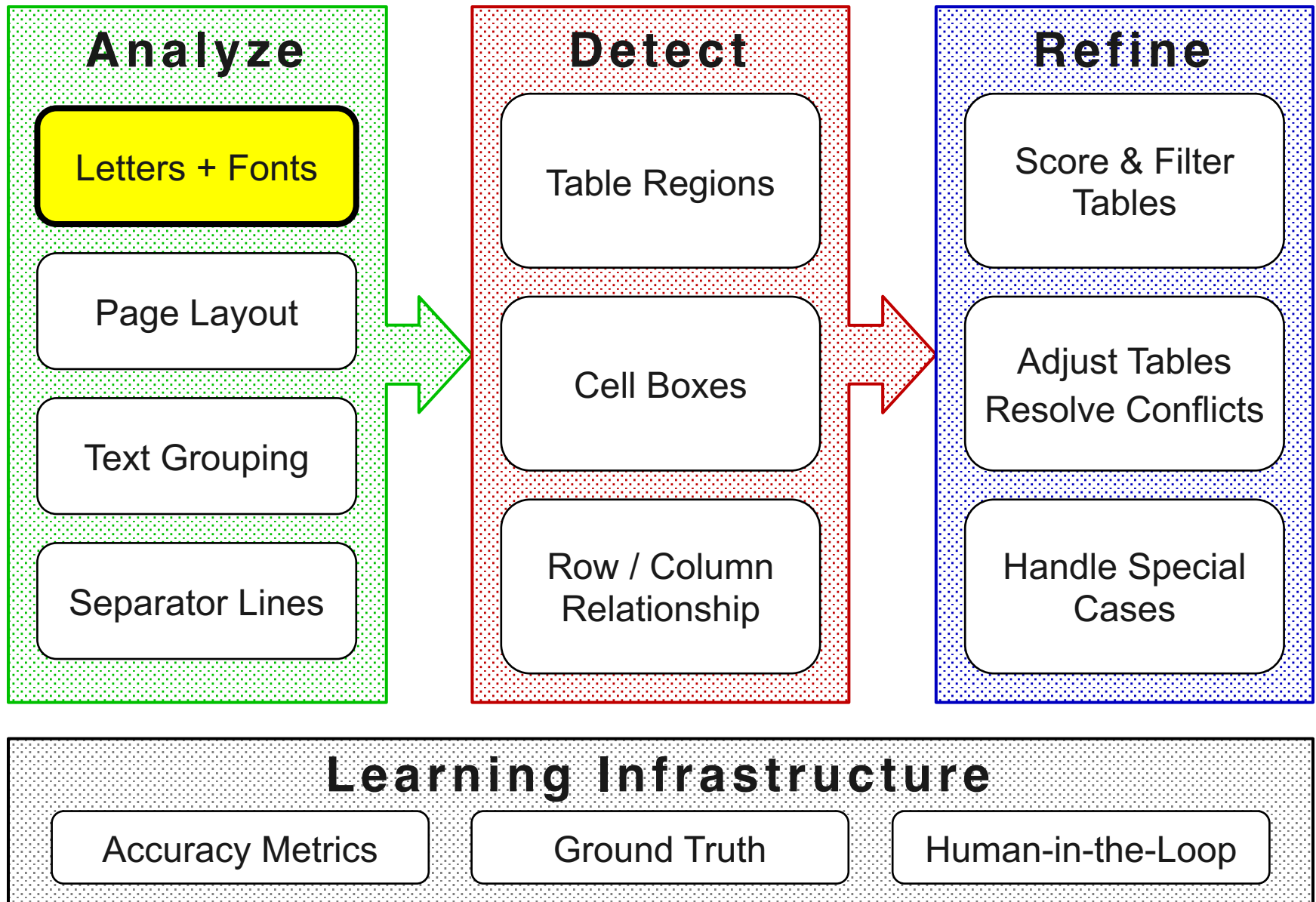
How to Build a Table Extraction System?

- **Analyze Page**
 - Read symbols & lines
 - Identify low-level structures & relations
 - Take shortcuts
- **The Main Tasks**
 - Table (region) detection
 - Cell structure recognition (given table region)
- **Refine Tables**
 - Discard false positives
 - Adjust table border and structure
 - Customer specific rules

Common Sub-Tasks in Table Extraction



Common Sub-Tasks in Table Extraction



Character Features

- Documents can be:
 - **scanned**
 - **programmatic** (“born digital” PDF, TXT)
 - **hybrid**
- **Scanned** pages are noisy:
 - Reverse any rotation, distortion
 - Filter noise, sharpen if low resolution [M19]
- Augment **OCR** output:
 - Fix inconsistent fonts, bounding boxes, highlighted text
 - Detect ruled lines and boxes
 - E.g., Gaussian filter + black hat transform [K13]



[K13] [T. Kasar et al. “Learning to Detect Tables in Scanned Document Images Using Line Information”, ICDAR ‘13](#)

[M19] [S. Mujumdar et al. “Simultaneous Optimisation of Image Quality Improvement and Text Content Extraction from Scanned Documents”, ICDAR ‘19](#)



Character Features

Tilt
Fuzzy Text

ORACLE

SERVICES AGREEMENT

The Services Agreement (the "Agreement") is between Oracle Corporation with its principal place of business at 500 Oracle Parkway, Redwood City, California 94065 ("Oracle") and IBM Corporation (legal name) with its principal place of business at Kingston, NY 12401 ("Client").

I. **Services**
Oracle will provide to Client, in the United States, the Services specified on a Work Order, under the terms of this Agreement.

II. **Definitions**

2.1. "Work Order" shall mean Oracle's standard form for ordering Services (entitled "Work Order" or "Order Form") and shall specify the Services and applicable fees. Each Work Order shall be governed by the terms of this Agreement and shall reference the Effective Date specified below.

2.2. "Services" shall mean work performed by Oracle for Client pursuant to a Work Order, agreed to by the parties, under this Agreement. The schedule for Services will be agreed upon by the parties, subject to availability of Oracle personnel.

III. **Charges, Payment, and Taxes**

3.1. **Fees for Services**

Unless otherwise expressly specified in the applicable Work Order, Services shall be provided on a time and material ("T&M") basis at Oracle's T&M rates current when the Services are performed. If a dollar limit is stated in the applicable Work Order for T&M Services, the limit shall be deemed an estimate for Client's budgeting and Oracle's resource scheduling purposes; after the limit is expended, Oracle will continue to provide the Services on a T&M basis, if a Work Order for continuation of the Services is signed by the parties.

3.2. **Incidental Expenses**

Client shall reimburse Oracle for reasonable travel, communications, and out-of-pocket expenses incurred in conjunction with the Services.

Agreement and/or any Work Order shall not limit either party from pursuing any other remedies available to it, including injunctive relief, nor shall termination relieve Client of its obligations to pay all charges that accrued prior to such termination.

V. **Infringement, Warranty, Remedy, and Limitation of Liability**

5.1. **Infringement Indemnity**

A. Each party ("Provider") will defend and indemnify the other party ("Recipient") against a claim that any information, design, specification, instruction, software, data, or material furnished by the Provider ("Material") and used by the Recipient for the Services infringe a United States copyright or patent provided that: (a) the Recipient notifies the Provider in writing within thirty (30) days of the claim; (b) the Provider has sole control of the defense and all related settlement negotiations; and (c) the Recipient provides the Provider with the assistance, information, and authority reasonably necessary to perform the above; reasonable out-of-pocket expenses incurred by the Recipient in providing such assistance will be reimbursed by the Provider.

B. The Provider shall have no liability for any claim of infringement resulting from: (a) the Recipient's use of a superseded or altered release of some or all of the Material; if infringement would have been avoided by the use of a subsequent unaltered release of the Material which is provided to the Recipient; or (b) any information, design, specification, instruction, software, data, or material not furnished by the Provider.

Rotated
Image

Agreement # 4912639376

Technical Services Agreement

Supplier will provide Deliverables and Services as specified in the relevant SOW and/or W.A. Supplier will begin work only after receiving a W.A. from Buyer. Buyer may request changes to a SOW and/or W.A. and Supplier will submit to Buyer the impact of such changes. Changes accepted by Buyer will be specified in an amended SOW and/or W.A. or change order signed by both parties. Supplier agrees to accept all W.A.'s that conform with the terms and conditions of this Agreement.

3.0 Pricing

Supplier will provide Deliverables and Services to Buyer for the Prices. The Prices for Deliverables and Services specified in a SOW and/or W.A. and accepted by Buyer plus the payment of applicable Taxes will be the only amount due to Supplier from Buyer. The relevant SOW or W.A. shall contain Prices for each country receiving Deliverables and Services under this Agreement. Supplier is not entitled to payment under this Agreement for activities also covered by a Business Partner Agreement with Buyer.

4.0 Taxes

Supplier's invoices shall state all applicable Taxes, if any, by tax jurisdiction and with a proper breakdown between taxable and non-taxable Deliverables and Services. Supplier assumes responsibility to timely remit all Tax payments to the appropriate governmental authority in each respective jurisdiction. Supplier and Buyer agree to cooperate to minimize, wherever possible and appropriate, any applicable Taxes and provide reasonable notice and cooperation in connection with any audit. Supplier shall also bear sole responsibility for all taxes, assessments, or other levies on its own income, based on purchased property, equipment or software. If Buyer provides a direct pay certificate, certification of an exemption from Tax or reduced rate of Tax imposed by an applicable taxing authority, then Supplier agrees not to invoice or pay any such Tax unless and until the applicable taxing authority assesses such Tax, at which time Supplier shall invoice and Buyer agrees to pay any such Tax that is legally owed.

Per capita poultry consumption

Country	Chicken consumption (kg/capita/year)	GDP/capita ⁽¹⁾ (US\$)	Population (m)
Malaysia	37.3	10,060	28.6
Singapore	36.2	49,945	5.2
Thailand	12.5	5,070	68.2
China	9.2	5,460	1,321.0
Philippines	8.4	2,210	101.8
Vietnam	7.2	1,380	88.6
Indonesia	6.1	3,448	245.6
India	2.3	1,540	1,202.0

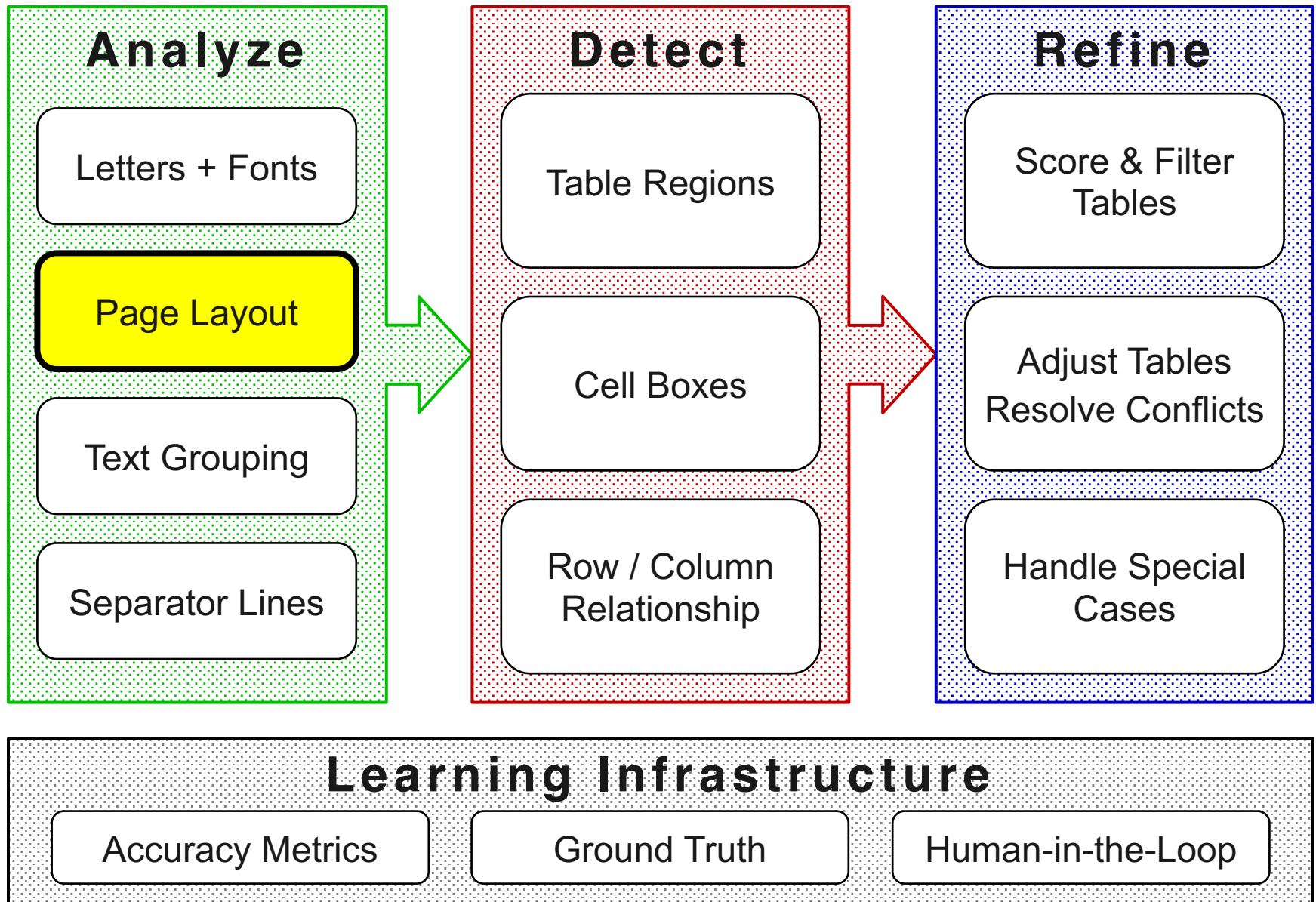
Potential upside
for chicken
consumption vs
"matured"
Malaysian market

Colored Background
Unclear Font Sizes

Character Features

- **Programmatic PDFs** (and TXTs)
 - Have letters, but **no** table markup
- May contain **spurious** (invisible) text and lines
 - White-on-white lines or text
 - Occluded or out-of-range lines or text
 - Text repeated to simulate bold font
 - **Need to filter them out**
- Deep Learning (CNN-based) methods need an image
 - Convert programmatic to scanned

Common Sub-Tasks in Table Extraction



Layout Analysis

- Plain text layout (1-column, 2-column, etc.)
 - Helps avoid false-positive “tables”
- Obvious non-tables
 - Page headers, footers, margins, numbering
 - Section headers
 - Lists, charts, highlighting
- Low-level structure
 - **Alignment** @ different box positions & tolerance levels
 - A minimum spanning tree for clustering by distance
- Deep learning features
 - Natural language embeddings

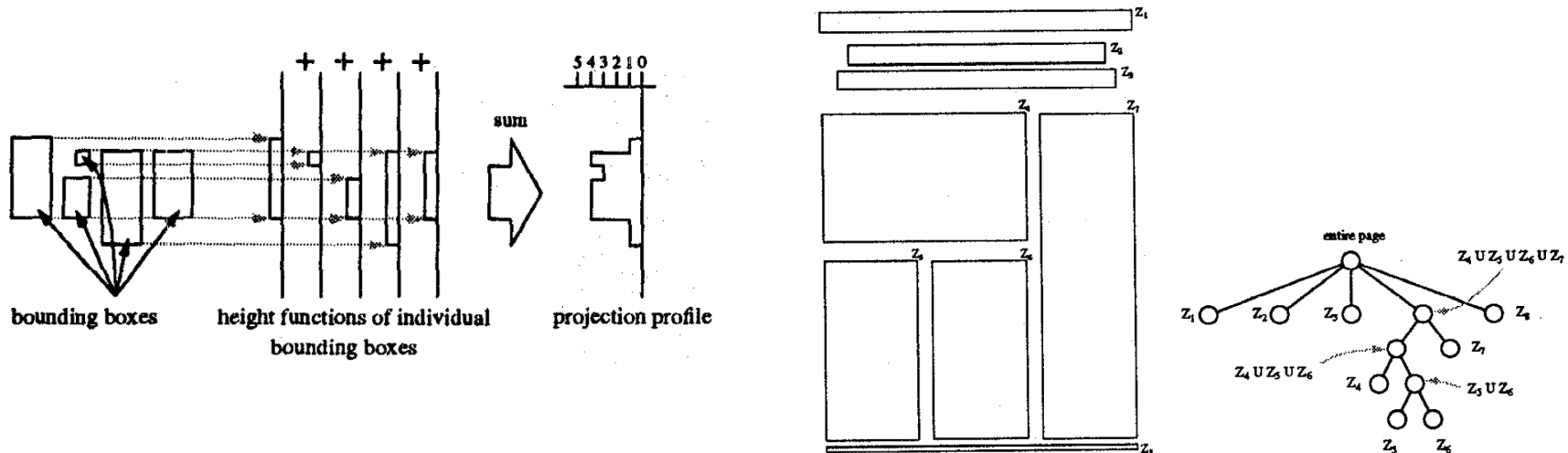
Text Alignment

Tab-Stops

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	Q4	Q3	Q2	Q1	Q4	Q3	Q2	Q1
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Change in non-cash working capital	(18,865)	(996)	5,452	8,923	(11,758)	(266)	1,958	1,949
Abandonment costs	6,177	3,189	697	1,346	1,760	814	434	962
Funds flow from operations	68,178	80,199	73,429	70,050	55,934	62,304	63,227	48,644
Weighted average outstanding shares (000s)								
- Basic	193,497	176,318	134,291	125,730	125,629	125,620	125,620	125,620
- Diluted	193,497	177,003	135,437	126,129	126,245	125,620	125,620	125,620
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(\$000s)						2014		2013
Cash flow from operating activities						285,933		234,256
Change in non-cash working capital						(5,486)		(8,117)
Abandonment costs						11,409		3,970
Funds flow from operations						291,856		230,109
Weighted average outstanding shares (000s)								
- Basic						157,697		125,622
- Diluted						157,697		125,778

Recursive X-Y Cut Algorithm

- Commonly used to partition page and generate separators
 - By [C02], [W04], [K14], and others
- [H95] The algorithm recursively, for each block:
 - Computes X- and Y-axis projection profiles
 - Divides the block into sub-blocks based on dips in profiles:



[H95] [J. Ha et al. "Recursive X-Y Cut Using Bounding Boxes of Connected Components", ICDAR '95](#)

[C02] [F. Cesarini et al. "Trainable Table Location in Document Images", ICPR '02](#)

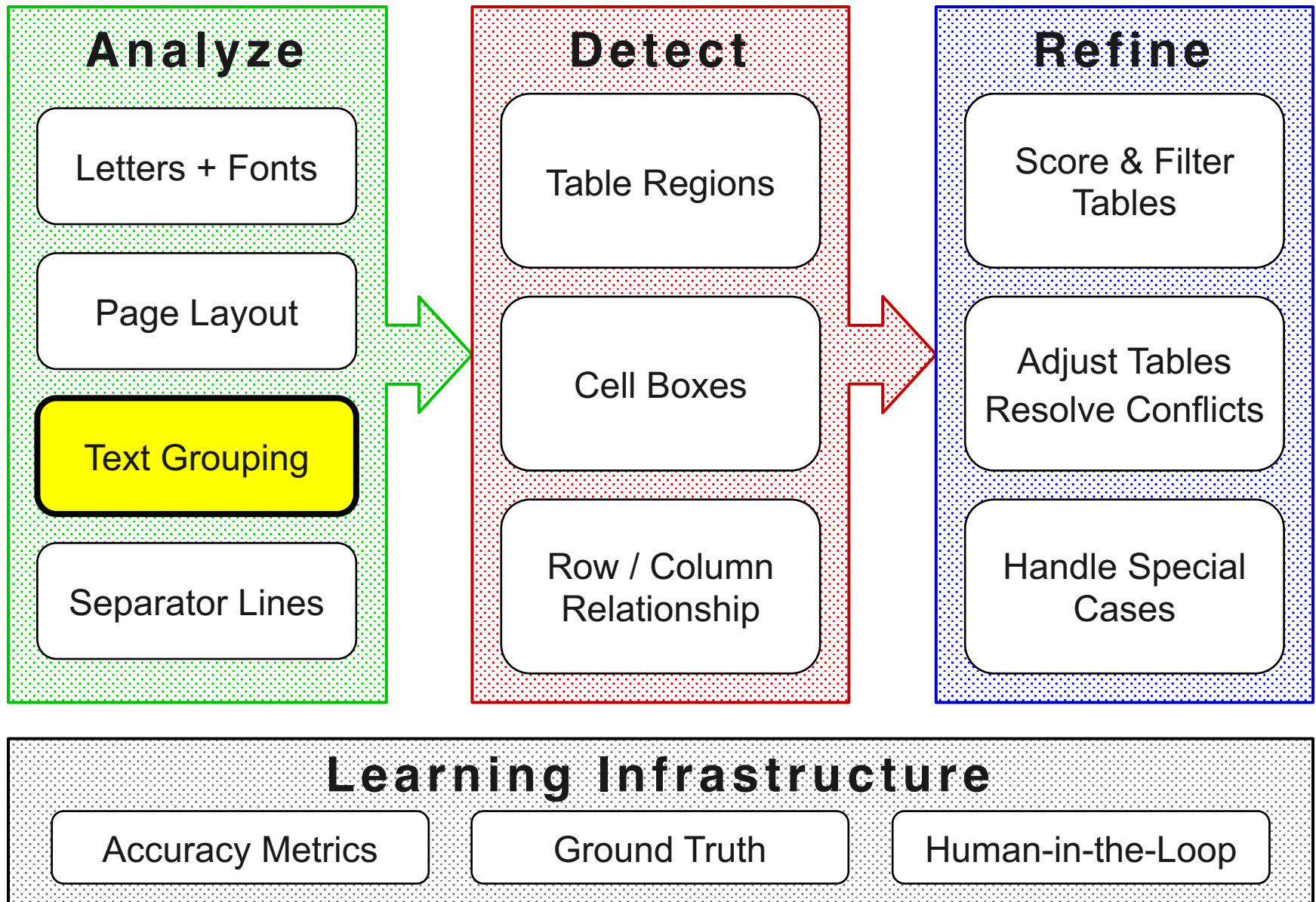
[W04] [Y. Wang et al. "Table Structure Understanding and Its Performance Evaluation", Pattern Recog. '04](#)

[K14] [S. Klampfl et al. "A Comparison of Two Unsupervised Table Recognition Methods from Digital Scientific Articles", D-Lib Mag. '14](#)

Short-Cuts

- No tables \Rightarrow **take a short-cut**
 - Pre-trained CNNs can be slow
 - Most pages have no tables \Rightarrow major time savings
- Detect obvious non-tables
 - Solid plain text, 1- or 2-column layout
 - Frames, lists, header / footer, comments on margins
- Detect “easy” tables quickly
 - Ruling lines only tables
 - One-line-per-row aligned numerical tables
- No other structures \Rightarrow **take a short-cut**

Common Sub-Tasks in Table Extraction



Group Text into Larger Units

- Most systems group text early on
 - Table **detection** systems *may* skip text grouping
- Text is grouped in one of 3 ways:
 - Columns first
 - Rows first
 - “Blobs” or “paragraphs” first
- Some systems partition text using separator lines
 - **BUT:** “Blob” detection reduces over- / under-partitioning

Example

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- Diluted	0.35	0.45	0.54	0.56	0.44	0.50	0.50	0.39

Two
Tables

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Funds flow from operations	291,856	230,109
Weighted average outstanding shares (000s)		
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Columns

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Example

Rows

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Example

Multi-line
"Blobs"

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Start with Columns

Many systems detect columns first:

- T-Recs [KD98], Pdf2table [Y05], Lixto [HB07], Tesseract [SS10], smartFIX [D11]

Example – Tesseract [SS10] :

1. Detect X-axis “tab-stops” (alignment positions)
2. Group tokens between “tab-stops” horizontally into entries
3. Group entries of the same font vertically into column fragments
4. Group column fragments within page columns horizontally into table fragments
5. Group table fragments if columns match vertically into tables



[KD98] [T. Kieninger and A. Dengel. “The T-Recs Table Recognition and Analysis System”, DAS ‘98](#)
 [Y05] [B. Yildiz et al. “pdf2table: A Method to Extract Table Information from PDF Files”, IICAI ‘05](#)
 [HB07] [T. Hassan and R. Baumgartner. “Table Recognition and Understanding from PDF Files”, ICDAR ‘07](#)
 [SS10] [F. Shafait and R. Smith. “Table Detection in Heterogeneous Documents”, DAS ‘10](#)
 [D11] [F. Deckert et al. “Table Content Understanding in smartFIX”, ICDAR ‘11](#)

Example

Tab-Stops

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Column Fragments

Example

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Table
Fragments

Example

Table
Fragments

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Funds flow from operations	68,178	80,199	73,429	70,050	55,934	62,304	63,227	48,644
Weighted average outstanding shares (000s)								
- Basic	193,497	176,318	134,291	125,730	125,629	125,620	125,620	125,620
- Diluted	193,497	177,003	135,437	126,129	126,245	125,620	125,620	125,620
Funds flow from operations per share (\$/share)								
- Basic	0.35	0.45	0.55	0.56	0.45	0.50	0.50	0.39
- Diluted	0.35	0.45	0.54	0.56	0.44	0.50	0.50	0.39

Tables

(\$000s)	2014	2013
Cash flow from operating activities	285,933	234,256
Change in non-cash working capital	(5,486)	(8,117)
Abandonment costs	11,409	3,970
Funds flow from operations	291,856	230,109
Weighted average outstanding shares (000s)		
- Basic	157,697	125,622
- Diluted	157,697	125,778

Multi-Column Headers

Example

	2014				2013			
(\$000s)	Q4	Q3	Q2	Q1	Q4	Q3	Q2	Q1
Cash flow from operating activities	80,866	78,006	67,280	59,781	65,932	61,756	60,835	45,733
Change in non-cash working capital	(18,865)	(996)	5,452	8,923	(11,758)	(266)	1,958	1,949
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Start with Rows

Systems *with ML* often detect rows first

- Pinto-McCallum [P03], e Silva [S06], TableSeer [L08], PDF-TREX [OR09]

Typical process:

1. Identify text-lines
2. Train an ML classifier to label text-lines:
 - “Table Dense”, “Table Sparse”, “Table Header”, “Non-table”, etc.
 - ML = CRF [P03], HMM [S06], SVM [L08], etc.
3. Merge sparse rows into dense rows – get full table rows:
 - Merge up, down, or cluster around, by **row alignment** [H00a]
4. Combine table rows into tables



[H00a] [J. C. Handley. “Table Analysis for Multi-line Cell Identification”, SPIE Doc. Recog. & Retr. ‘00](#)

[P03] [D. Pinto et al. “Table Extraction Using Conditional Random Fields”, SIGIR ‘03](#)

[S06] [A. C. e Silva et al. “Design of an End-to-end Method to Extract Information from Tables”, IJDAR ‘06](#)

[L08] [Y. Liu et al. “Identifying Table Boundaries in Digital Documents via Sparse Line Detection”, CIKM ‘08](#)

[OR09] [E. Oro and M. Ruffolo. “PDF-TREX: An Approach for Recognizing and Extracting Tables from PDF Documents”, ICDAR ‘09](#)



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Table Header

Table Header

Sparse Row

Dense Row

Sparse Row

Dense Row

Dense Row

Sparse Row

Dense Row

Sparse Row

Sparse Row

Sparse Row

Dense Row

Dense Row

Sparse Row

Sparse Row

Sparse Row

Dense Row

Dense Row

Align-
ment



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Dense Row

Dense Row

Dense Row

Sparse Row

Sparse Row

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Dense Row

Sparse Row

Dense Row

Dense Row

Sparse Row

Dense Row

Heading Row

Heading Row

Heading Row

Dense Row

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Heading Row

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Heading Row

Dense Row

Dense Row

Align-
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Dense Row

Heading Row

Heading Row

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Table Header

Table Header

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Dense Row

Sparse Row

Dense Row

Dense Row

Sparse Row

Dense Row

Heading Row

Heading Row

Heading Row

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Dense Row

Heading Row

Heading Row

Heading Row

Dense Row

Dense Row

Align-
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Dense Row

Dense Row

Heading Row

Heading Row

Dense Row

Dense Row

“Blobs” (Phrases \leq Text-Lines \leq Paragraphs)

- “Blob” = largest semantically bound text unit
 - Single-line or multi-line
 - If in a table, the whole “blob” must be in a single cell
- “Blob” \neq Cell
 - Cell has **span** and **overlaps** other cells
 - Some “blobs” end up in plain text or non-table text
- “Blobs” help define table structure:
 - Trace alignment
 - Determine header cell spans
 - **Fix over-split / over-merged cells, rows, columns**
 - Reduce search space

How to Detect “Blobs”

- [KD98] Distance based clustering:
 - Merge words horizontally
 - Merge text strings vertically *if word-spans interleave*
- Problems with distance:
 - **Multi-column headers:** 1 justified phrase vs. ≥ 2 closely spaced phrases
 - **Row headers / text cells:** 1 multi-line cell vs. ≥ 2 closely spaced rows
- Example:

This	is	a	small
it	consists	of	
lines	-	enough	

	Two Column Header		Two Column Header	
HEADER	Header	Header	Header	Header
Row 1, text line 1	0.12	1.23	2.34	3.45
Row 1, text line 2				
Row 1, text line 3				
Row 2, text line 1	4.56	5.67	6.78	7.89
Row 2, text line 2				
Row 2, text line 3				



How to Detect “Blobs”

- [H00a], [OR09] Merge “sparse” rows into “dense” rows
 - Merge up, merge down, or cluster around
- [L09] Detect and follow reading order ← **an NLP challenge**
- [B12] [B14] Train a classifier over “blob” features:
 - Proper termination (e.g. “blobs” don’t end with a dash or comma)
 - Number of numeric strings
 - Indentation, large space at the end of a string
 - Shared font properties
- Deep learning approaches ← **see later in this tutorial**
 - Cell detection over image
 - Semantic relationship detection (over text) using BERT



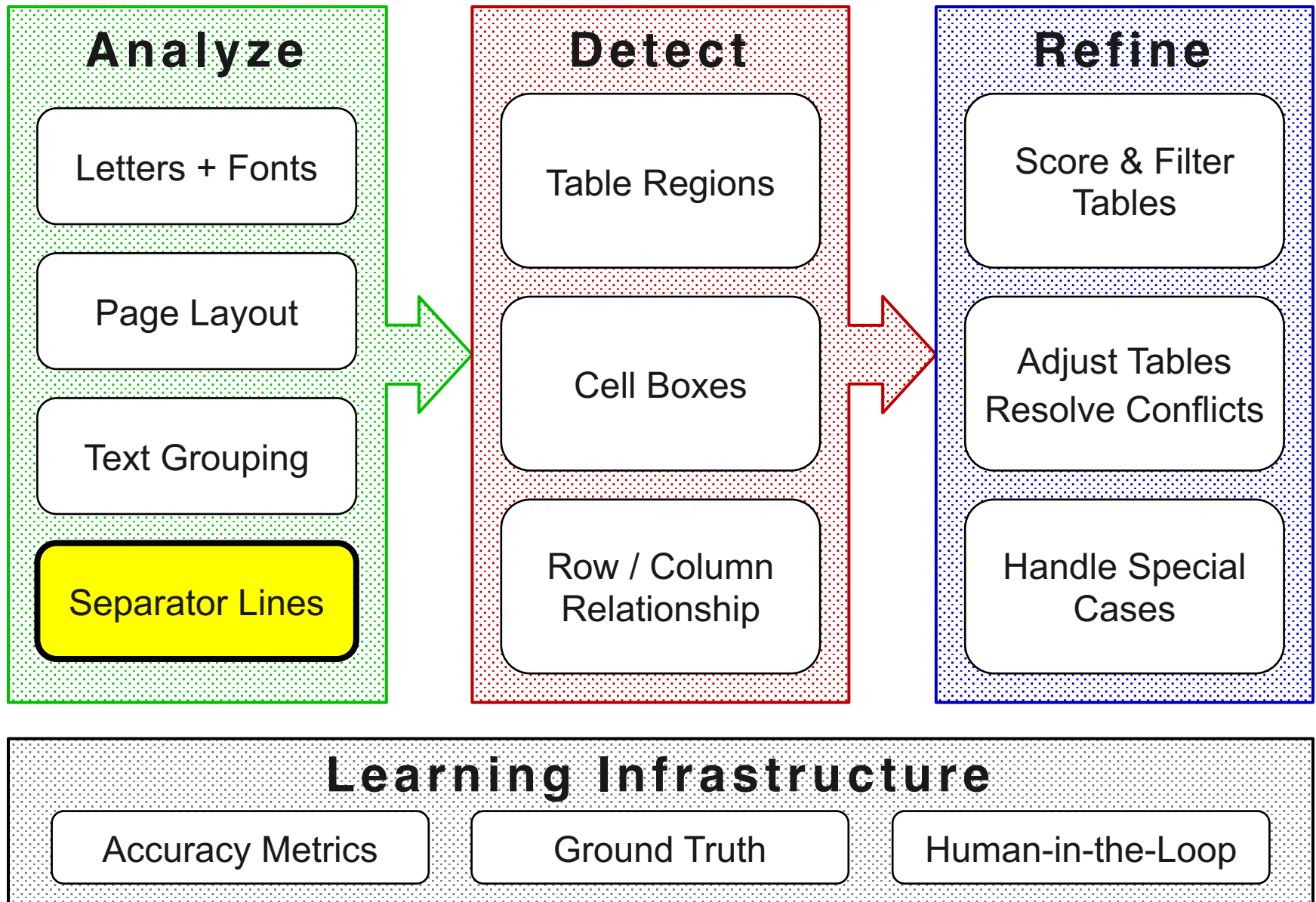
[H00a] [J. C. Handley. “Table Analysis for Multi-line Cell Identification”, SPIE Doc. Recog. & Retr. '00](#)
[OR09] [E. Oro and M. Ruffolo. “PDF-TREX: An Approach for Recognizing and Extracting Tables from PDF Documents”, ICDAR '09](#)
[L09] [Y. Liu et al. “Improving the Table Boundary Detection in PDFs by Fixing the Sequence Error of the Sparse Lines”, ICDAR '09](#)
[B12] [E. Bart. “Parsing Tables by Probabilistic Modeling of Perceptual Cues”, DAS '12](#)
[B14] [A. Bansal et al. “Table Extraction from Document Images using Fixed Point Model”, ICVGIP '14](#)



Example

Name and Principal Position	Year	Salary (\$) ⁽¹⁾	Bonus (\$) ⁽²⁾	Stock Awards (\$) ⁽³⁾	Non-Equity Incentive Plan Compensation (\$) ⁽¹⁾⁽⁴⁾	All Other Compensation (\$) ⁽⁵⁾	Total (\$)
Bob Sasser Chief Executive Officer	2015	\$1,585,577	—	\$5,803,264	\$2,080,320	\$ 60,549	\$ 9,529,710
	2014	\$1,505,769	—	\$4,104,531	\$2,140,773	\$ 63,415	\$ 7,814,488
	2013	1,410,577	—	3,839,768	1,909,929	58,089	\$ 7,218,363
Kevin Wampler Chief Financial Officer	2015	635,577	—	1,695,764	617,121	51,452	2,999,914
	2014	570,192	—	1,249,783	628,654	54,481	2,503,110
	2013	545,192	—	1,140,273	499,465	56,380	2,241,310
Gary Philbin President and Chief Operating Officer	2015	971,154	—	2,438,906	1,258,725	56,568	4,725,353
	2014	830,769	—	1,780,806	1,000,652	57,302	3,669,529
	2013	738,846	—	1,749,799	796,624	53,080	3,338,349
Robert H. Rudman Chief Merchandising Officer	2015	692,307	—	1,726,563	645,165	61,647	3,125,682
	2014	656,154	—	1,357,425	682,642	59,269	2,755,490
	2013	636,154	—	1,253,591	555,262	54,918	2,499,925
Michael Matacunas Chief Administrative Officer	2015	537,500	—	1,247,773	550,639	40,269	2,376,181
	2014	483,077	—	949,917	324,766	42,349	1,800,109
	2013	274,038	150,000	899,826	182,258	215,306	1,721,428
Howard Levine Former Chief Executive Officer of Family Dollar Stores	2015	666,388	—	—	—	11,838,299 ⁽⁶⁾	12,504,687
	2014						
	2013						

Common Sub-Tasks in Table Extraction



Separator Line Detection

- Ruled Lines & Colored Boxes

- Extend ruled lines over small gaps, “snap” together
- Merge touching colored boxes, **then** convert into lines
- Filter out: highlighting, underlining, boxed comments, logos, charts etc.

- **BUT:** A “perfect” ruled-line grid can be incomplete !

- Some lines may be **missing**
- Lines may **fail to extend** to header rows / columns



[CK93] [S. Chandran and R. Kasturi. “Structural Recognition of Tabulated Data”, ICDAR ‘93](#)

[I93] [K. Itonori. “Table Structure Recognition Based on Textblock Arrangement and Ruled Line Position”, ICDAR ‘93](#)

[F11] [J. Fang et al. “A Table Detection Method for Multipage PDF Documents via Visual Separators and Tabular Structures”, ICDAR ‘11](#)

[B12] [E. Bart. “Parsing Tables by Probabilistic Modeling of Perceptual Cues”, DAS ‘12](#)



Example 1

(Canadian dollars in millions, except where indicated)	Third Quarter		Change	
	2015	2014	\$	%
Aircraft fuel expense – GAAP	\$ 697	\$ 939	\$ (242)	(26)
Add: Aircraft fuel expense related to regional airline operations	95	137	(42)	(31)
Total Aircraft fuel expense	\$ 792	\$ 1,076	\$ (284)	(26)
Add: Net cash payments on fuel derivatives ⁽¹⁾	14	4	10	250
Economic cost of fuel – Non-GAAP ⁽²⁾	\$ 806	\$ 1,080	\$ (274)	(25)
Fuel consumption (thousands of litres)	1,289,911	1,200,017	89,894	7.5
Fuel cost per litre (cents) – GAAP	61.4	89.7	(28.3)	(31.5)
Economic fuel cost per litre (cents) – Non-GAAP ⁽²⁾	62.5	90.0	(27.5)	(30.6)

(Canadian dollars in millions, except where indicated)	First Nine Months		Change	
	2015	2014	\$	%
Aircraft fuel expense – GAAP	\$ 1,937	\$ 2,567	\$ (630)	(25)
Add: Aircraft fuel expense related to regional airline operations	278	389	(111)	(29)
Total Aircraft fuel expense	\$ 2,215	\$ 2,956	\$ (741)	(25)
Add: Net cash payments on fuel derivatives ⁽¹⁾	36	6	30	500
Economic cost of fuel – Non-GAAP ⁽²⁾	\$ 2,251	\$ 2,962	\$ (711)	(24)
Fuel consumption (thousands of litres)	3,442,909	3,220,893	222,016	6.9
Fuel cost per litre (cents) – GAAP	64.3	91.8	(27.4)	(29.9)
Economic fuel cost per litre (cents) – Non-GAAP ⁽²⁾	65.4	91.9	(26.6)	(28.9)

Example 2

Minimum Number of Accessible Parking Spaces

ADA Standards for Accessible Design 4.1.2 (5)

Total Number of Parking spaces Provided (per lot)	Total Minimum Number of Accessible Parking Spaces (60" & 96" aisles)	Van Accessible Parking Spaces with min. 96" wide access aisle	Accessible Parking Spaces with min. 60" wide access aisle
	Column A		
1 to 25	1	1	0
26 to 50	2	1	1
51 to 75	3	1	2
76 to 100	4	1	3
101 to 150	5	1	4
151 to 200	6	1	5
201 to 300	7	1	6
301 to 400	8	1	7
401 to 500	9	2	7
501 to 1000	2% of total parking provided in each lot	1/8 of Column A*	7/8 of Column A**
1001 and over	20 plus 1 for each 100 over 1000	1/8 of Column A*	7/8 of Column A**

* one out of every 8 accessible spaces

** 7 out of every 8 accessible parking spaces

Example 3

course	material type	row						
Java	prob. & anim. exam.		prob. ID	prob. name	prob. topic	anim. exam. topic	anim. exam. name	anim. exam. ID
		1	14	jArrayList5	ArrayList	ArrayList	ae_arraylist2_v2	3
		2	18	jBoolean_Operators	Boolean expressions	Switch	ae_switch_demo2	44
		3	65	jMathFuc2	Arithmetic operations	Arithmetic operations	ae_arithmetic_v2	1
		4	100	jWhile1	Loops while	Loops while	ae_while_demo	49
	prob. & annot. exam.		prob. ID	prob. name	prob. topic	annot. exam. topic	annot. exam. name	annot. exam. ID
		5	37	jDowhile1	Loops do_while	Loops for	for1_v2	28
		6	57	jInterfaces1	Interfaces	Variables	PrintTester	78
		7	61	jInterfaces5	Interfaces	Objects	AccessorMutatorDemo	1
		8	63	jMathCeil	Arithmetic operations	Loops for	JavaTutorial4_6_8	57
Python	prob. & annot. exam.		prob. ID	prob. name	prob. topic	annot. exam. topic	annot. exam. name	annot. exam. ID
		9	3	q_py_arithmetic1	Variables	Variables	pyt1.3	5
		10	21	q_py_nested_if_elif1	if_statements	values_references	pytt10.25	58
		11	23	q_py_obj_account1	classes_objects	Lists	pyt7.2	53
	prob. & anim. exam.		prob. ID	prob. name	prob. topic	anim. exam. topic	anim. exam. name	anim. exam. ID
		12	7	q_py_dict_access1	dictionary	loops	ae_adl_while	39
		13	29	q_py_output1	output_formatting	variables	ae_adl_arithmetics2	1
		14	10	q_py_fun_car1	functions	exceptions	ae_adl_tryexcept2	34
	prob. & pars. prob.		prob. ID	prob. name	prob. topic	pars. prob. topic	pars. prob. name	pars. prob. ID
		15	10	q_py_fun_car1	functions	exceptions	ps_python_try_adding	38
		16	12	q_py_if_elif1	if_statements	loops	combo_python_while	9
		17	35	q_py_swap1	variables	variables	combo_swap	11
	pars. prob. & annot. exam.		pars. prob. ID	pars. prob. name	pars. prob. topic	annot. exam. topic	annot. exam. name	annot. exam. ID
		18	1	combo_avg	variables	variables	pyt2.1	32
		19	14	ps_python_addition	variables	variables	pyt1.2	4
		20	41	ps_return_bigger_or_none	functions	functions	pyt10.7	30
	pars. prob. & anim. exam.		pars. prob. ID	pars. prob. name	pars. prob. topic	anim. exam. topic	anim. exam. name	anim. exam. ID
		21	1	combo_avg	variables	variables	ae_python_assignment	40
		22	12	ps_hello	variables	variables	ae_adl_arithmetics2	1
		23	43	ps_simple_params	functions	functions	ae_adl_returnvalue	29

Separator Line Detection

- White-space separators (“virtual” lines)
 - Help define cell span / cell alignment in tables
 - **Prune false-positives** by ML or by heuristics [B12]
- How to detect white-space separators
 - Cell-unit (“blob”) bounding box expansion [I93]
 - Axis projection histograms [CK93]
 - White-space cover by maximum-area white-space rectangles [F11]
- How to prune separators (features to use)
 - **Adjacent text “blobs”** : alignment, size, and content
 - **Other separators** that run parallel to, or **intersect**, the separator



[CK93] [S. Chandran and R. Kasturi. “Structural Recognition of Tabulated Data”, ICDAR ‘93](#)

[I93] [K. Itonori. “Table Structure Recognition Based on Textblock Arrangement and Ruled Line Position”, ICDAR ‘93](#)

[F11] [J. Fang et al. “A Table Detection Method for Multipage PDF Documents via Visual Separators and Tabular Structures”, ICDAR ‘11](#)

[B12] [E. Bart. “Parsing Tables by Probabilistic Modeling of Perceptual Cues”, DAS ‘12](#)



Common Sub-Tasks in Table Extraction

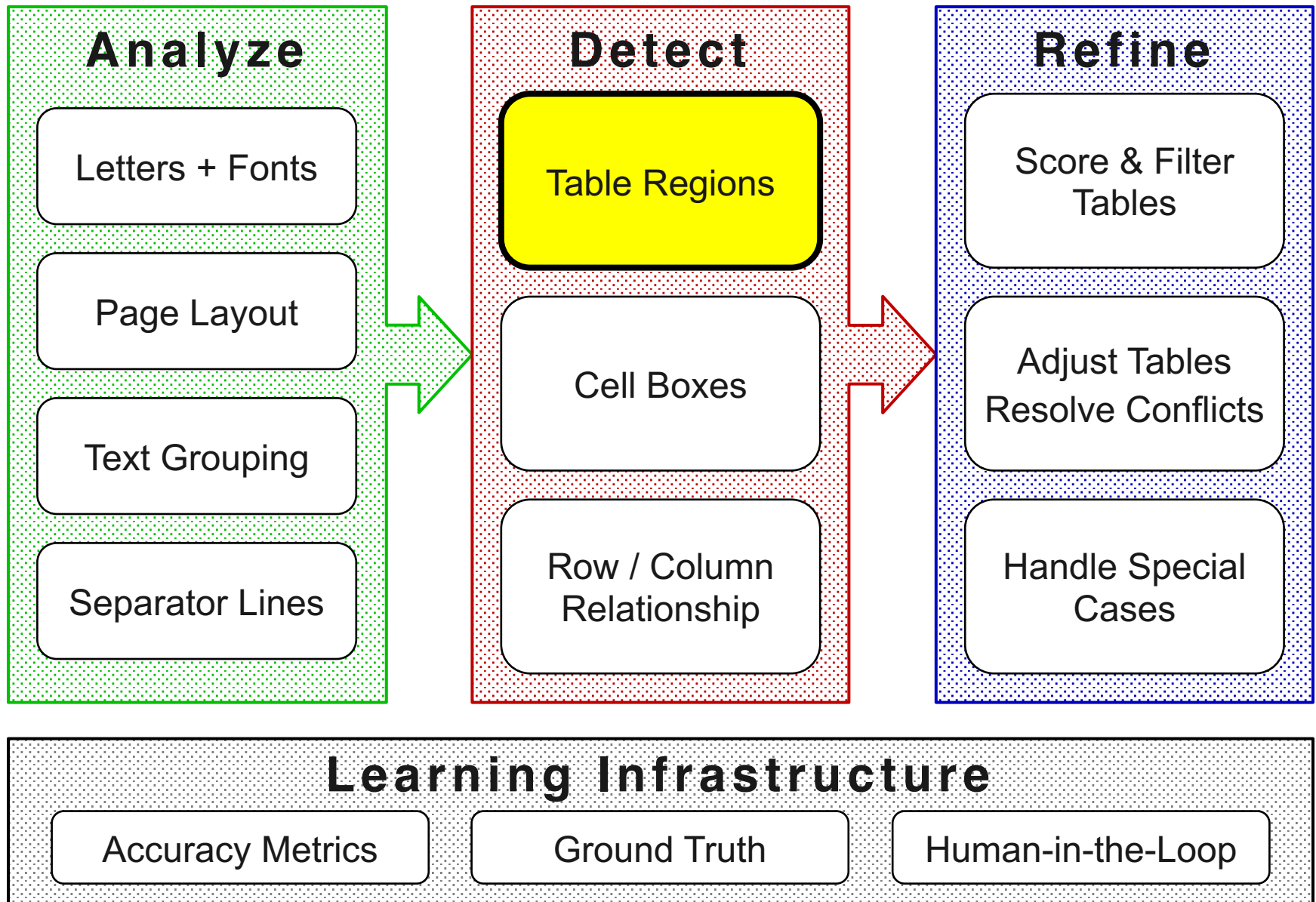


Table Detection Overview

- **(Pre-DL)** Find elements of tables and group them to find the whole table (rows/columns, blobs or lines first)
- **(CNN-based)** Try a fixed set of table region proposals from object detection
 - CNN shares computation of features across all translations of a given proposal rectangle
 - Proposal rectangle shapes / sizes are fixed as hyperparameters
 - If a proposal hits a table, a regression decides table borders



[CL12] [J. Chen and D. Lopresti. "Model-Based Tabular Structure Detection and Recognition in Noisy Handwritten Documents", ICFHR '12](#)
[B14] [A. Bansal et al. "Table Extraction from Document Images using Fixed Point Model", ICVGIP '14](#)
[G17] [A. Gilani et al. "Table Detection using Deep Learning", ICDAR '17](#)
[S18b] [S. A. Siddiqui et al. "DeCNT: Deep Deformable CNN for Table Detection", IEEE Acc. '18](#)



Detect Candidate Table Regions (pre-DL)

- **Ruled Line grids** / frames, connected components
- **(Rows 1st)** Stack “table” rows whose “blobs” co-align [L08], [OR09]
 - Rows are labeled by an ML-classifier (CRF, SVM, HMM)
 - Labels & matching “blob” layout → table regions
 - **NOTE:** Be sure to label “header rows” to tell tables apart !
- **(Cols 1st)** Cluster overlapping column fragments [HB07], [SS10]
 - Group table columns horizontally, staying within page layout columns (when possible)
 - Group vertically if column fragments overlap, match, or subsume
 - **NOTE:** Column header areas require special handling !



[HB07] [T. Hassan and R. Baumgartner. “Table Recognition and Understanding from PDF Files”, ICDAR ‘07](#)

[L08] [Y. Liu et al. “Identifying Table Boundaries in Digital Documents via Sparse Line Detection”, CIKM ‘08](#)

[OR09] [E. Oro and M. Ruffolo. “PDF-TREX: An Approach for Recognizing and Extracting Tables from PDF Documents”, ICDAR ‘09](#)

[SS10] [F. Shafait and R. Smith. “Table Detection in Heterogeneous Documents”, DAS ‘10](#)

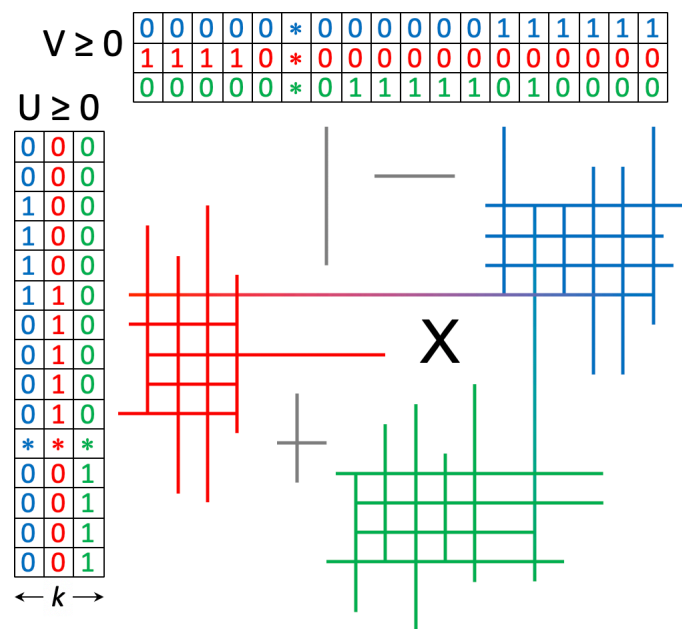
[K13] [T. Kasar et al. “Learning to Detect Tables in Scanned Document Images Using Line Information”, ICDAR ‘13](#)



Detect Candidate Table Regions (pre-DL)

- **(Blobs 1st)** Classify text “blobs”, cluster those labeled “table”
 - [B14] iteratively labels “blobs” **given their neighbors’ labels**
 - [B14] trains a Kernel Logistic Regression classifier
- **(Lines 1st)** Find areas where “strong” separators make a grid
 - [CL12] uses Max-Flow / Min-Cut algorithm to extract grids
 - Bi-cluster the intersection matrix of horizontal vs. vertical separators
 - Example: Non-neg. matrix factorization for grid clustering (right)

Non-neg. Matrix Factorization for Grid Clustering



Deep Learning for Table Detection

Use existing object detection frameworks (Faster R-CNN or YOLO) retrained for table detection

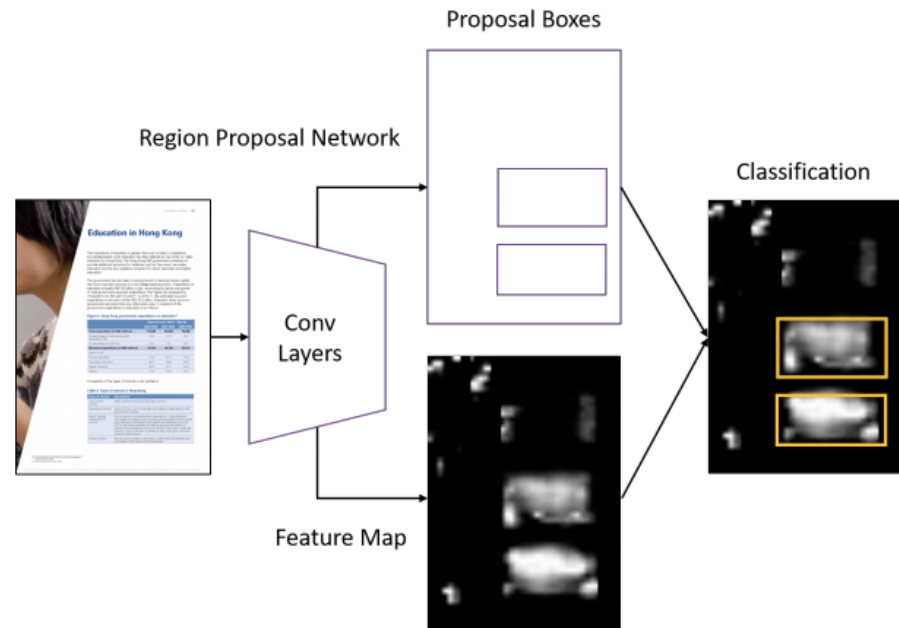


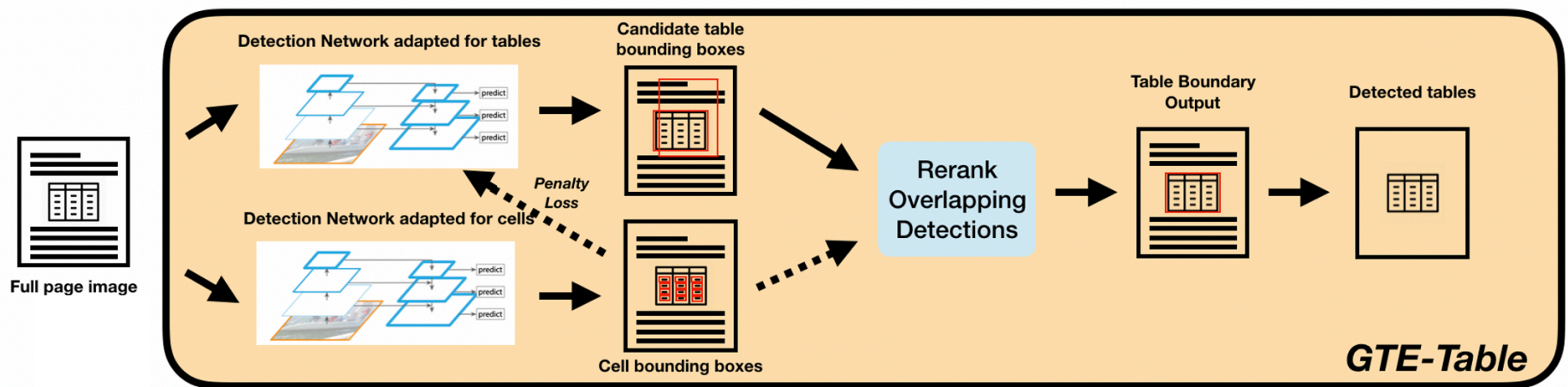
Figure 5: The Faster R-CNN model for table detection



- [G17] [A. Gilani et al. "Table Detection using Deep Learning", ICDAR '17](#)
- [S17] [Schreiber et al. "DeepDeSRT: Deep Learning for Detection and Structure Recognition of Tables in Document Images" ICDAR '17](#)
- [S18a] [P. Staar et al. "Corpus Conversion Service: A Machine Learning Platform to Ingest Documents at Scale", KDD '18](#)
- [L20] [Li et al. "TableBank: Table Benchmark for Image-based Table Detection and Recognition". LREC '20](#)
- [Z20a] [Zheng et al. "Global Table Extractor \(GTE\): A Framework for Joint Table Identification and Cell Structure Recognition Using Visual Context", arXiv 2020](#)
- [P20a] [D. Prasad et al. "CascadeTabNet: An Approach for End to End Table Detection and Structure Recognition from Image-Based Documents", In CVPR Workshops 2020](#)
- [P20b] [Paliwal et al. "TableNet: Deep Learning Model for End-to-end Table Detection and Tabular Data Extraction from Scanned Document Images", arXiv 2020](#)

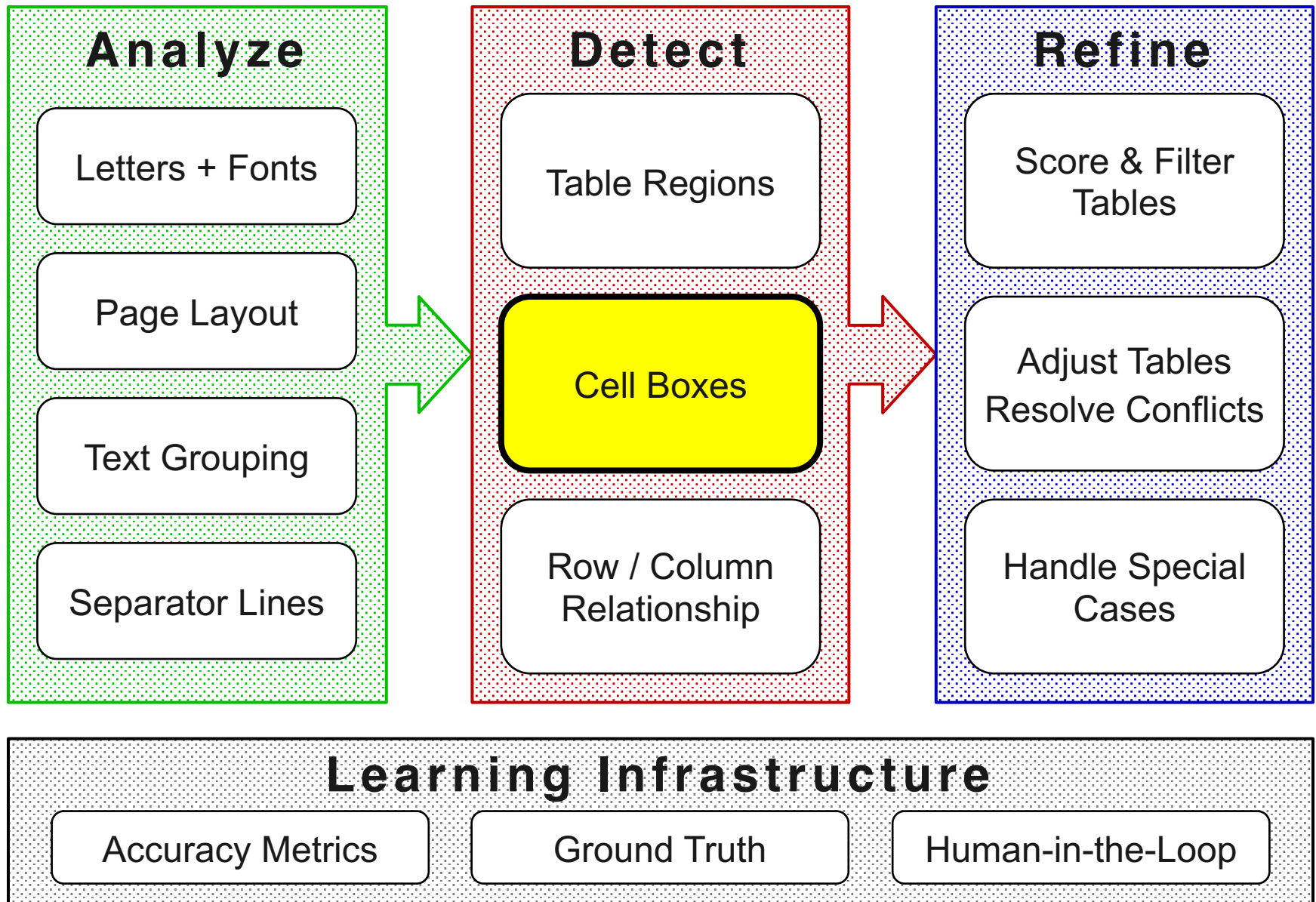
GTE-table

Leverage spatial containment relationship between tables and cells to improve table object recognition



Zheng et al. Global Table Extractor (GTE): A Framework for Joint Table Identification and Cell Structure Recognition Using Visual Context, arXiv 2020

Common Sub-Tasks in Table Extraction



Cell Detection – Overview

- Pre-DL approaches:

- Just use text “blobs” as cells
- Iteratively merge “blobs” sharing columns & rows [H00a] [OR09]
- Use separator lines to define cells [B12]

- Deep Learning approaches:

- Detect cells over image using object detection CNNs [Z20a] [P20a]



[H00a] [J. C. Handley. “Table Analysis for Multi-line Cell Identification”, SPIE Doc. Recog. & Retr. '00](#)

[OR09] [E. Oro and M. Ruffolo. “PDF-TREX: An Approach for Recognizing and Extracting Tables from PDF Documents”, ICDAR '09](#)

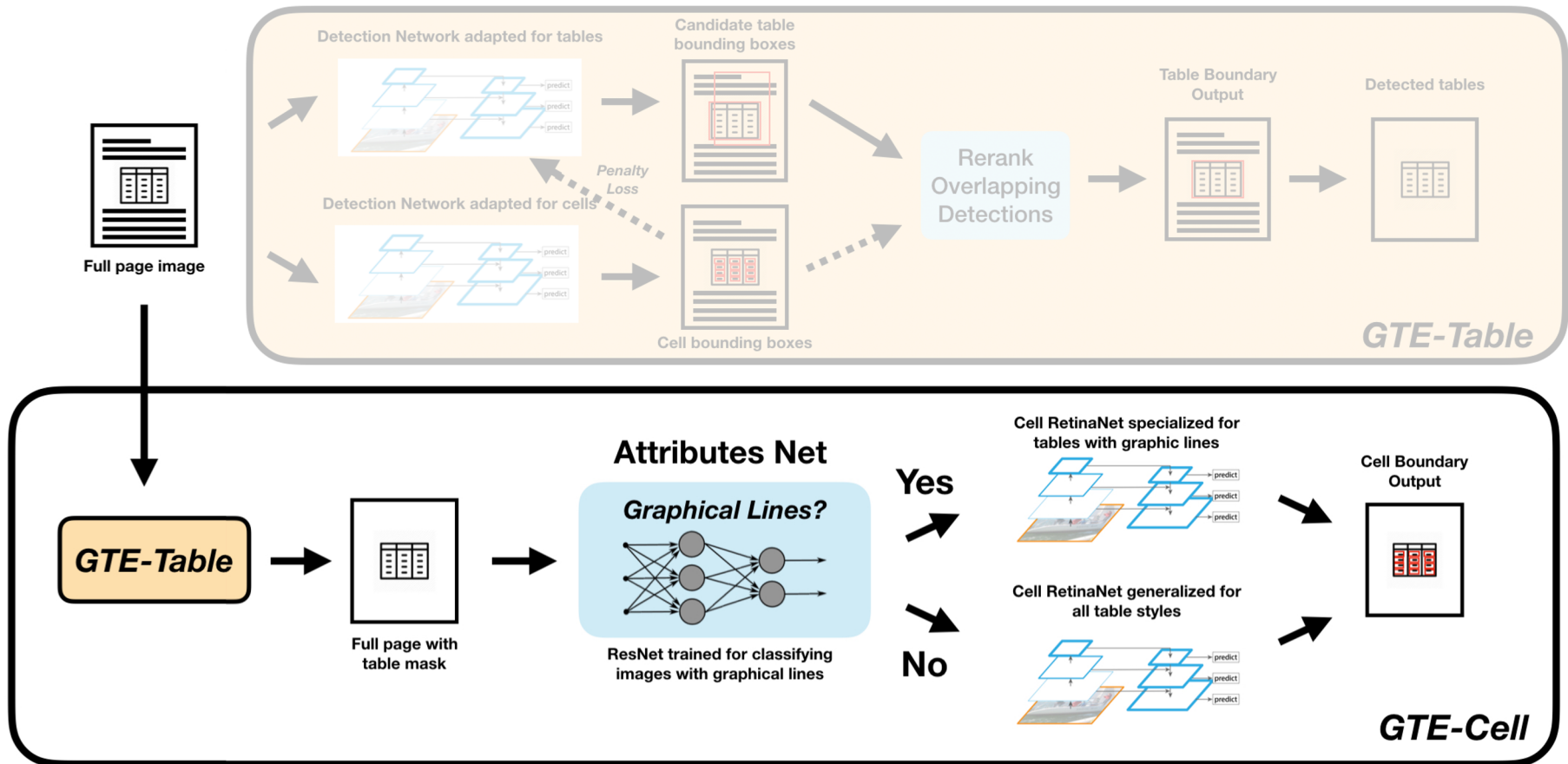
[B12] [E. Bart. “Parsing Tables by Probabilistic Modeling of Perceptual Cues”, DAS '12](#)

[Z20a] [Zheng et al. Global Table Extractor \(GTE\): A Framework for Joint Table Identification and Cell Structure Recognition Using Visual Context, arXiv 2020](#)

[P20a] [D. Prasad et al. CascadeTabNet: An approach for end to end table detection and structure recognition from image-based documents. In CVPR Workshops 2020.](#)

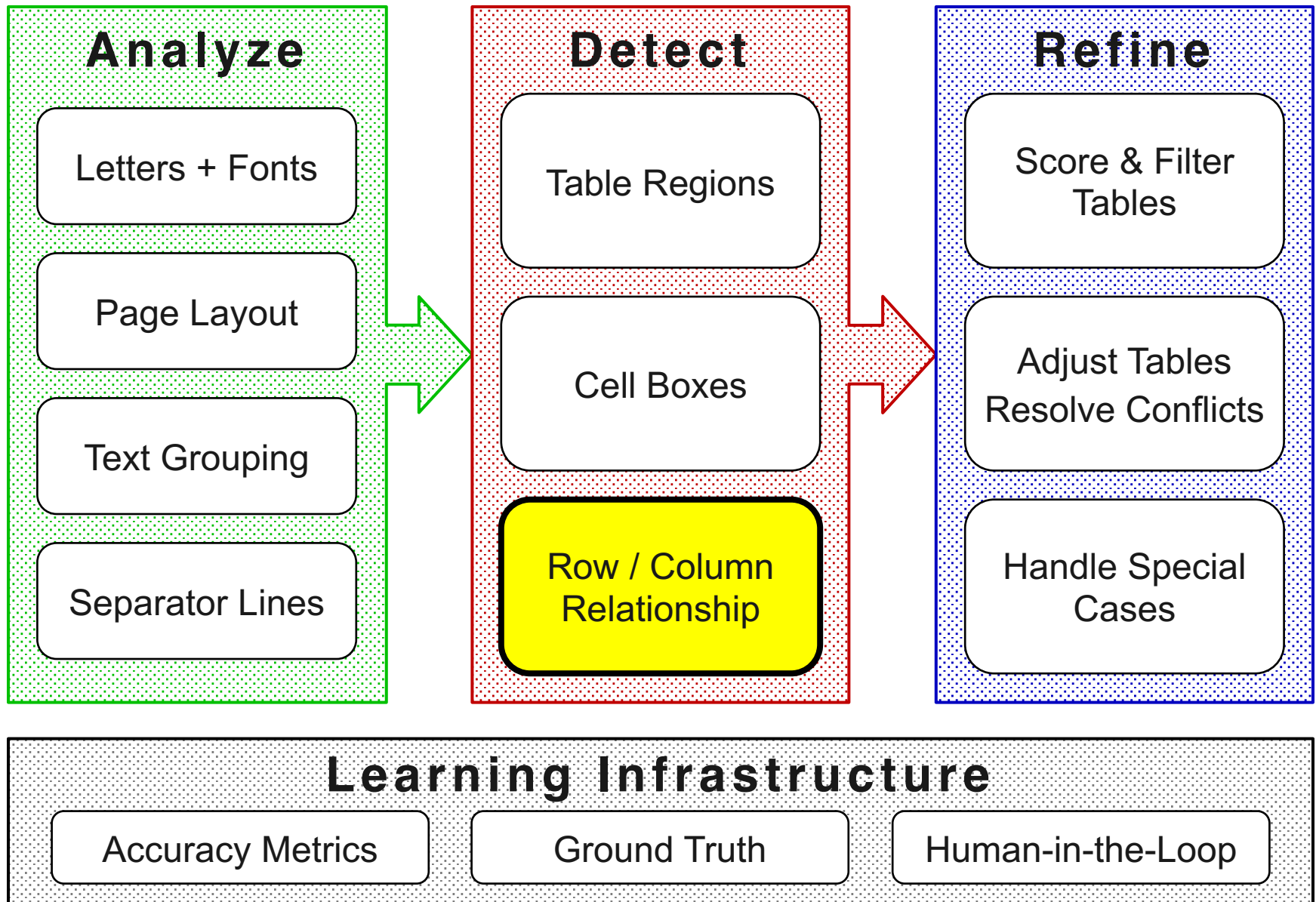
GTE Cell

Hierarchical deep learning system that pays attention to the global table style before cell detection



[Zheng et al. Global Table Extractor \(GTE\): A Framework for Joint Table Identification and Cell Structure Recognition Using Visual Context, arXiv 2020](#)

Common Sub-Tasks in Table Extraction



Cell Structure: Overview

- Cell structure defines:
 - Rows and Columns
 - Precedence order within each row and column
- Ways to specify cell structure:
 - **Separator lines:** Define cell spans across rows and columns
 - **Graphs over cells:** Define same-row and same-column relations
 - **Cell boxes:** Define row and column spans for each cell
 - **Text based:** Define cell structure using structured code output,
 - Such as HTML, XML

Cell Structure: Line Based

- Cell borders \leftarrow ruled lines \cup “strong” white-space lines
 - **Extend lines** to make rectangular cells, avoid crossing “blobs”
- **Ruled-line grids:** test for incompleteness
 - Multiple numerics per cell
 - A “strong” white-space line splits text in ≥ 2 cells
 - A “mini-table” inside a ruled cell
 - Cell structure extends beyond table frame
- **White-space grids:** clean up empty cells
 - Expand header cells by merging with empty cells [S06]
 - Merge (almost-) empty rows and columns

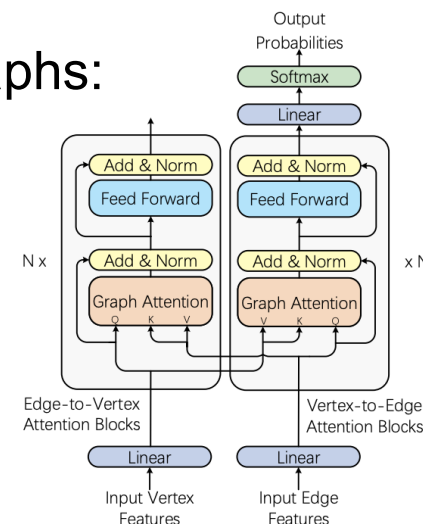


[S06] [A. C. e Silva et al. “Design of an End-to-end Method to Extract Information from Tables”, IJDAR '06](#)

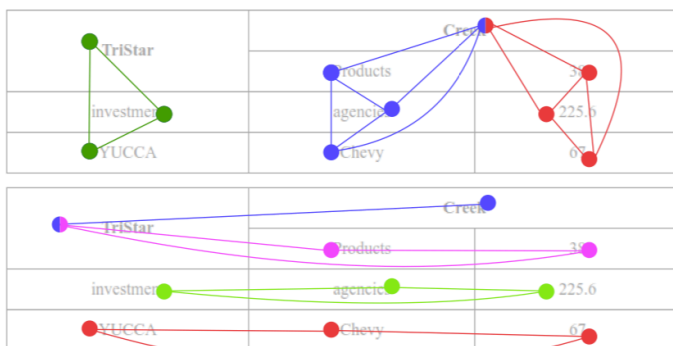
[B12] [E. Bart. “Parsing Tables by Probabilistic Modeling of Perceptual Cues”, DAS '12](#)

Cell Structure: Graph Based

- Use **Spatial Constraints** to find an overlap DAG over cells [H03]
- Use **Graph Neural Networks** to find 2 *undirected* graphs:
 - “Same Row” graph & “Same Column” graph
 - Two cells share an edge \Leftrightarrow share a row / a column
 - [Q19]: Rows and columns = **maximal cliques**
 - [C19]: Only adjacent cells share a graph edge

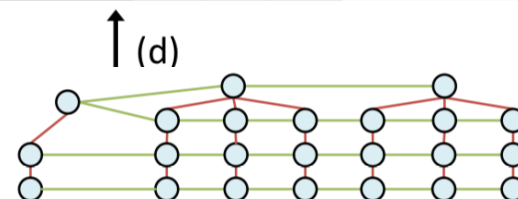


[Q19]



[C19]

Method	D1			D2		
	P	R	F1	P	R	F1
A	0.5	0.5	0.5	0.1	0.1	0.1
B	0.3	0.3	0.3	0.2	0.2	0.2



- [H03] [M. Hurst. “A Constraint-based Approach to Table Structure Derivation”, ICDAR ‘03](#)
 [Q19] [S. R. Qasim et al. “Rethinking Table Recognition using Graph Neural Networks”, 2019](#)
 [C19] [Z. Chi et al. “Complicated Table Structure Recognition”, arXiv, 2019](#)
 [L20] [Y Li et al. “GFTE: Graph-based Financial Table Extraction”, arXiv, 2020](#)

- | by education system: 2011 | | | | | by education system: 2011 | | | | | |
|---------------------------|---|---|---|--|--|------------------------|---|---|---|--|
| Education system | Percentage of population aged 25 and over | Percentage of population aged 25 and over with tertiary education | Weighted average participation rate in tertiary education | Weighted average participation rate in tertiary education by a proficiency level | Weighted average participation rate in tertiary education by a proficiency level | Education system | Percentage of population aged 25 and over | Percentage of population aged 25 and over with tertiary education | Weighted average participation rate in tertiary education | Weighted average participation rate in tertiary education by a proficiency level |
| Albania | 100 | 100 | 100 | 100 | 100 | Albania | 100 | 100 | 100 | 100 |
| Algeria | 100 | 100 | 100 | 100 | 100 | Algeria | 100 | 100 | 100 | 100 |
| Angola | 100 | 100 | 100 | 100 | 100 | Angola | 100 | 100 | 100 | 100 |
| Argentina | 100 | 100 | 100 | 100 | 100 | Argentina | 100 | 100 | 100 | 100 |
| Australia | 100 | 100 | 100 | 100 | 100 | Australia | 100 | 100 | 100 | 100 |
| Austria | 100 | 100 | 100 | 100 | 100 | Austria | 100 | 100 | 100 | 100 |
| Azerbaijan | 100 | 100 | 100 | 100 | 100 | Azerbaijan | 100 | 100 | 100 | 100 |
| Bahrain | 100 | 100 | 100 | 100 | 100 | Bahrain | 100 | 100 | 100 | 100 |
| Bangladesh | 100 | 100 | 100 | 100 | 100 | Bangladesh | 100 | 100 | 100 | 100 |
| Barbados | 100 | 100 | 100 | 100 | 100 | Barbados | 100 | 100 | 100 | 100 |
| Belarus | 100 | 100 | 100 | 100 | 100 | Belarus | 100 | 100 | 100 | 100 |
| Belgium | 100 | 100 | 100 | 100 | 100 | Belgium | 100 | 100 | 100 | 100 |
| Belize | 100 | 100 | 100 | 100 | 100 | Belize | 100 | 100 | 100 | 100 |
| Bhutan | 100 | 100 | 100 | 100 | 100 | Bhutan | 100 | 100 | 100 | 100 |
| Bolivia | 100 | 100 | 100 | 100 | 100 | Bolivia | 100 | 100 | 100 | 100 |
| Bosnia and Herzegovina | 100 | 100 | 100 | 100 | 100 | Bosnia and Herzegovina | 100 | 100 | 100 | 100 |
| Brazil | 100 | 100 | 100 | 100 | 100 | Brazil | 100 | 100 | 100 | 100 |
| Bulgaria | 100 | 100 | 100 | 100 | 100 | Bulgaria | 100 | 100 | 100 | 100 |
| Burkina Faso | 100 | 100 | 100 | 100 | 100 | Burkina Faso | 100 | 100 | 100 | 100 |
| Burundi | 100 | 100 | 100 | 100 | 100 | Burundi | 100 | 100 | 100 | 100 |
| Cambodia | 100 | 100 | 100 | 100 | 100 | Cambodia | 100 | 100 | 100 | 100 |
| Cameroon | 100 | 100 | 100 | 100 | 100 | Cameroon | 100 | 100 | 100 | 100 |
| Canada | 100 | 100 | 100 | 100 | 100 | Canada | 100 | 100 | 100 | 100 |
| Cape Verde | 100 | 100 | 100 | 100 | 100 | Cape Verde | 100 | 100 | 100 | 100 |
| Chad | 100 | 100 | 100 | 100 | 100 | Chad | 100 | 100 | 100 | 100 |
| Chile | 100 | 100 | 100 | 100 | 100 | Chile | 100 | 100 | 100 | 100 |
| China | 100 | 100 | 100 | 100 | 100 | China | 100 | 100 | 100 | 100 |
| Colombia | 100 | 100 | 100 | 100 | 100 | Colombia | 100 | 100 | 100 | 100 |
| Costa Rica | 100 | 100 | 100 | 100 | 100 | Costa Rica | 100 | 100 | 100 | 100 |
| Cote d'Ivoire | 100 | 100 | 100 | 100 | 100 | Cote d'Ivoire | 100 | 100 | 100 | 100 |
| Croatia | 100 | 100 | 100 | 100 | 100 | Croatia | 100 | 100 | 100 | 100 |
| Cuba | 100 | 100 | 100 | 100 | 100 | Cuba | 100 | 100 | 100 | 100 |
| Cyprus | 100 | 100 | 100 | 100 | 100 | Cyprus | 100 | 100 | 100 | 100 |
| Czechia | 100 | 100 | 100 | 100 | 100 | Czechia | 100 | 100 | 100 | 100 |
| Dominican Republic | 100 | 100 | 100 | 100 | 100 | Dominican Republic | 100 | 100 | 100 | 100 |
| Dominica | 100 | 100 | 100 | 100 | 100 | Dominica | 100 | 100 | 100 | 100 |
| Dominican Republic | 100 | 100 | 100 | 100 | 100 | Dominican Republic | 100 | 100 | 100 | 100 |
| Dominica | 100 | 100 | 100 | 100 | 100 | Dominica | 100 | 100 | 100 | 100 |
| Dominican Republic | 100 | 100 | 100 | 100 | 100 | Dominican Republic | 100 | 100 | 100 | 100 |
| Dominica | 100 | 100 | 100 | 100 | 100 | Dominica | 100 | 100 | 100 | 100 |
| Dominican Republic | 100 | 100 | 100 | 100 | 100 | Dominican Republic | 100 | 100 | 100 | 100 |
| Dominica | 100 | 100 | 100 | 100 | | | | | | |



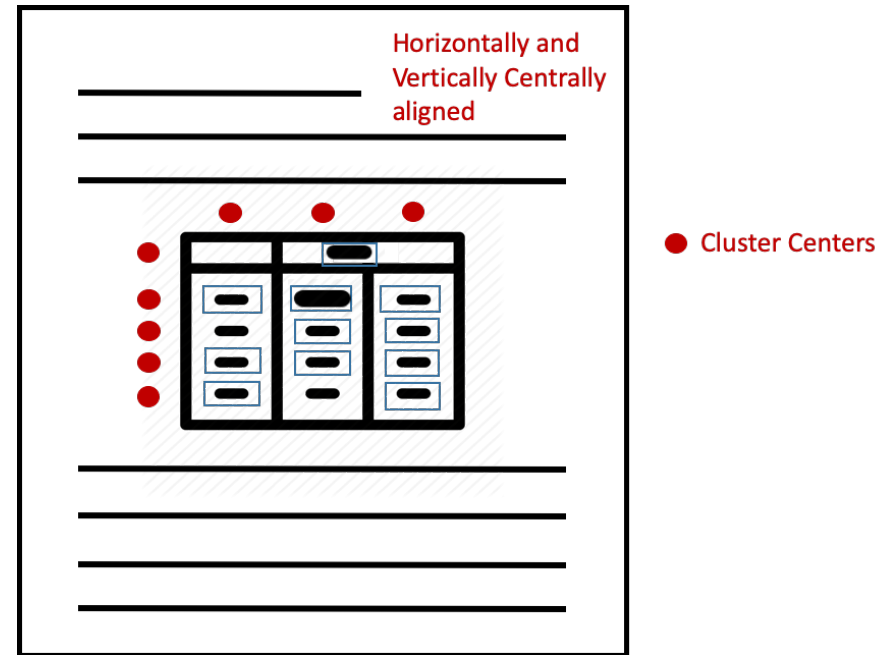
[T19] Tensmeyer et al. “Deep splitting and merging for table structure decomposition” ICDAR 2019

[K19] Khan et al. "Table Structure Extraction with Bi-directional Gated Recurrent Unit Networks" ICDAR 2019

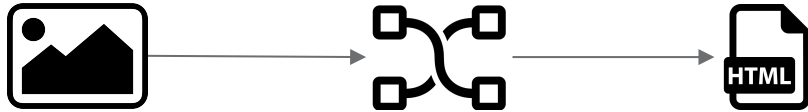


Cell Structure: Spatial clustering of cell units with language post-processing (GTE)

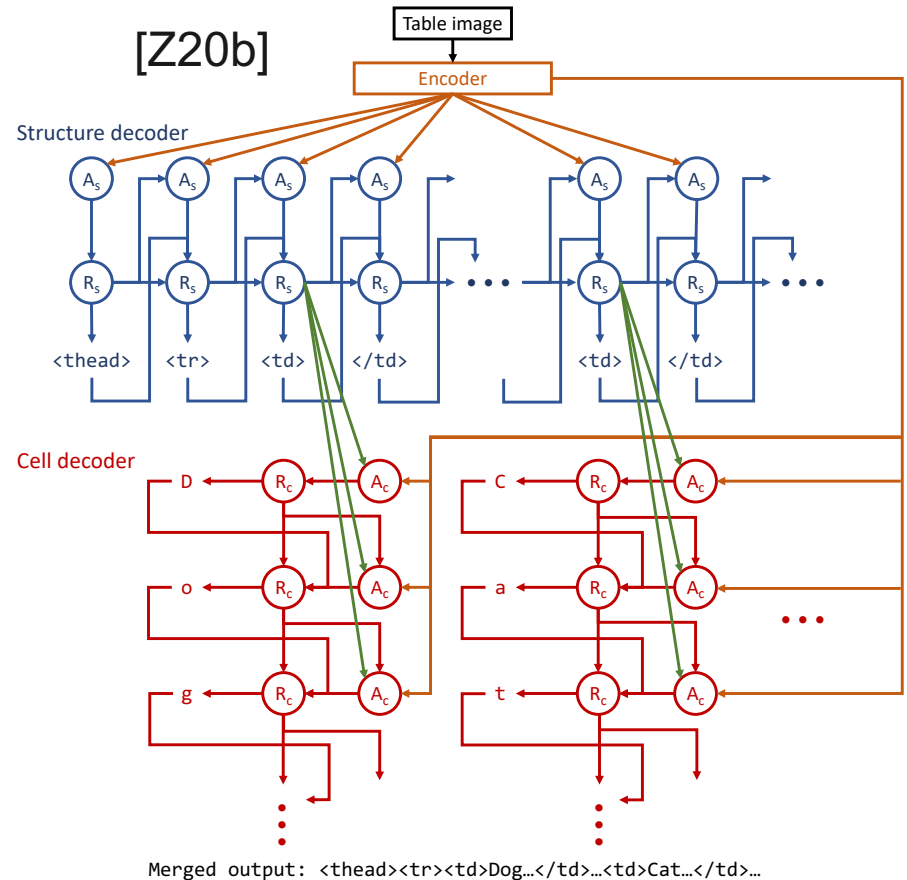
1. Cluster detected cells into rows and columns based on x-y coordinate and detected alignment.
2. Merge and split result based on textual clues (capitalization, special symbols etc.)



Cell Structure: Language Generation Based



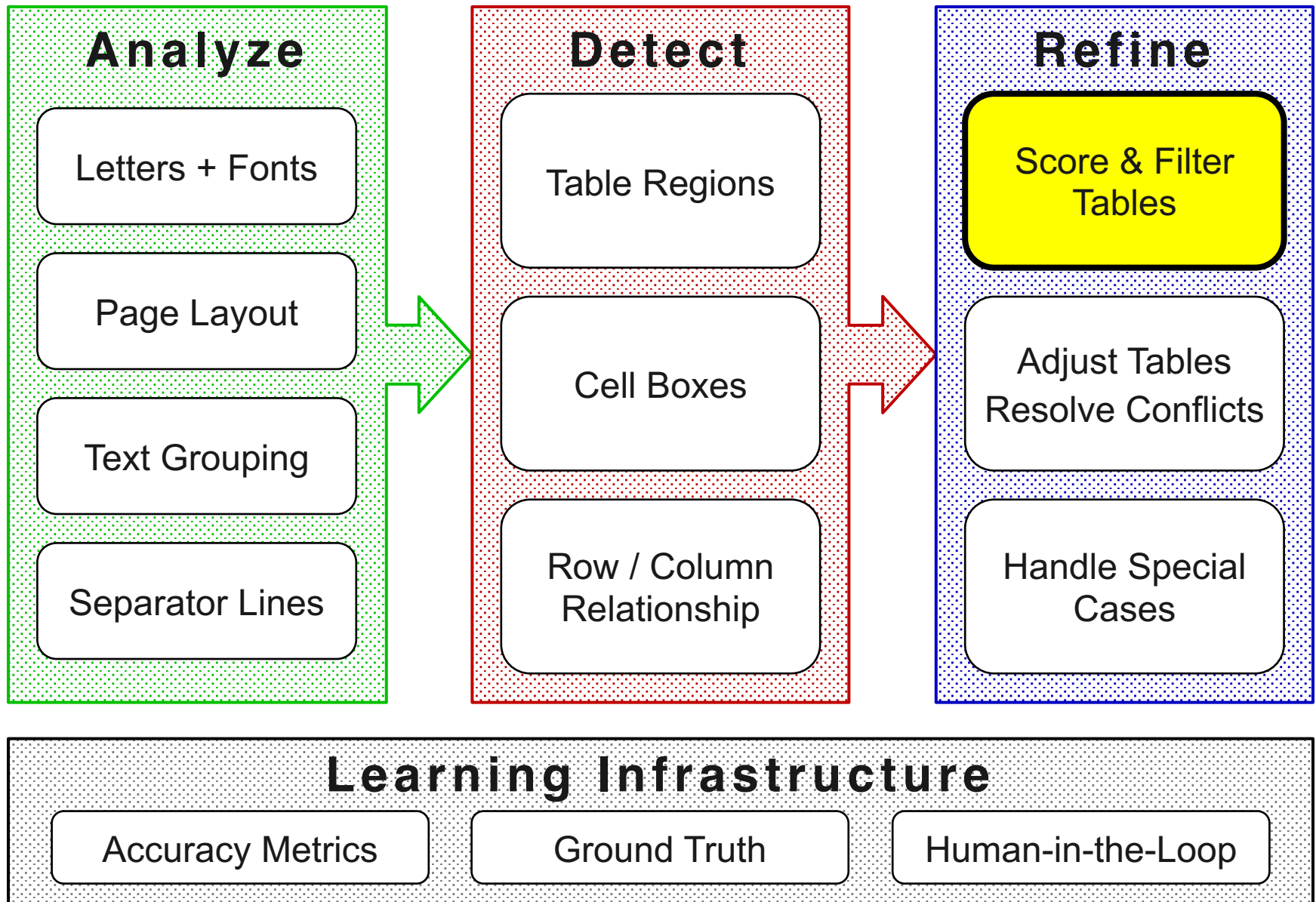
Recurrent neural network to encode image and then decode text of html representation of image



[L20] [Li et al. "TableBank: Table Benchmark for Image-based Table Detection and Recognition". LREC 2020](#)

[Z20b] [Zhong et al. "Image-based table recognition: data, model, and evaluation", ECCV 2020](#)

Common Sub-Tasks in Table Extraction



Why Scoring Tables?

- Eliminate false positive tables
- Detect (and fix) malformed table regions
 - Plain text in tables
 - Missing row / column headers or split-off pieces
 - One region covers multiple tables
- Compare alternative table candidates
 - Example: Is this 1 table or 2 tables?
- Improve table region and structure
 - Pick the best adjustment out of a range of options
 - Given cell structure, fix table region

Table Scoring Challenges

- Tables are **very** diverse
 - Tiny or huge, misaligned, text in cells, key-value pairs, confusing delimiters
 - Complex row / column headers – so different, **easy to chop off !**
- What's **around** the table also matters
 - Can its columns or rows be extended? Should they be?
- One table, or ≥ 2 adjacent tables?
 - **1 table may have:** ruled bars, wide gaps, font / alignment changes
 - **2 tables may be:** fully or partly co-aligned, separated in one of many ways
- Non-table text can have structure, too
 - Page headers / footers, framed / highlighted text, hierarchical lists, ...

Example 1

Part 2 Financial claims scheme

4AA Support that is not external support

- (1) For subsection 11CA (1C) of the Act, a form of support that is entered into in the normal course of business is not to be considered external support for the purposes of subsection 11CA (1B) of the Act.
- (2) For subsection 13A (1A) of the Act, a form of support that is entered into in the normal course of business is not to be considered external support for the purposes of paragraph 13A (1) (b) of the Act.
- (3) For subsection 13E (3) of the Act, a form of support that is entered into in the normal course of business is not to be considered external support for the purposes of paragraph 13E (1) (b) of the Act.

NOT A TABLE !

4A Clearance period

For subsection 16AF (1) of the Act, 5 business days is the prescribed period of clearance.

5 Financial claims scheme — limit on payments

- (1) For subsection 16AG (1) of the Act, a limit of \$1 000 000 is prescribed.
- (2) For the purpose of determining the prescribed limit on the payments to the account-holder, if the amount held in the account is expressed as a foreign currency, it must be converted to Australian dollars using the daily exchange rate published by the Reserve Bank of Australia.

Example 2

Row
headers

Column
headers

A summary of the impact of these items on EPS is as follows:

(in millions, except per share data)

	Pre-Tax Income/(Loss)	Tax Benefit/ (Expense) ⁽¹⁾	After-Tax Income/(Loss)	EPS Favorable/ (Adverse) ⁽²⁾
Year Ended September 29, 2018:				
Net benefit from the Tax Act	\$ —	\$ 1,701	\$ 1,701	\$ 1.11
Gain from sale of real estate, property rights and other	601	(158)	443	0.30
Impairment of equity investments	(210)	49	(161)	(0.11)
Restructuring and impairment charges	(33)	7	(26)	(0.02)
Total	<u>\$ 358</u>	<u>\$ 1,599</u>	<u>\$ 1,957</u>	<u>\$ 1.28</u>
Year Ended September 30, 2017:				
Settlement of litigation	\$ (177)	\$ 65	\$ (112)	\$ (0.07)
Restructuring and impairment charges	(98)	31	(67)	(0.04)
Gain related to the acquisition of BAMTech	255	(93)	162	0.10
Total	<u>\$ (20)</u>	<u>\$ 3</u>	<u>\$ (17)</u>	<u>\$ (0.01)</u>
Year Ended October 1, 2016:				
Vice Gain	\$ 332	\$ (122)	\$ 210	\$ 0.13
Restructuring and impairment charges	(156)	43	(113)	(0.07)
Infinity Charge ⁽³⁾	(129)	47	(82)	(0.05)
Total	<u>\$ 47</u>	<u>\$ (32)</u>	<u>\$ 15</u>	<u>\$ 0.01</u>

Example 3

Depreciation expense is as follows:

(in millions)

Media Networks
Cable Networks
Broadcasting
Total Media Networks
Parks and Resorts
Domestic
International
Total Parks and Resorts
Studio Entertainment
Consumer Products & Interactive Media
Corporate
Total depreciation expense

Column
headers

	2018	2017	2016
\$	172	\$ 137	\$ 147
	92	88	90
	264	225	237
	1,410	1,336	1,273
	742	660	445
	2,152	1,996	1,718
	55	50	51
	69	63	63
	218	252	251
\$	2,758	\$ 2,586	\$ 2,320

Amortization of intangible assets is as follows:

(in millions)

Media Networks
Parks and Resorts
Studio Entertainment
Consumer Products & Interactive Media
Total amortization of intangible assets

Row
headers

	2018	2017	2016
\$	62	\$ 12	\$ 18
	4	3	3
	64	65	74
	123	116	112
\$	253	\$ 196	\$ 207

Example 4

As at, or for the 12-month periods ended, March 31 (\$ in millions)

Components of debt and coverage ratios

Net debt ¹
EBITDA – excluding restructuring and other costs ²
Net interest cost ³
Debt ratio
Net debt to EBITDA – excluding restructuring and other costs
Coverage ratios
Earnings coverage ⁵
EBITDA – excluding restructuring and other costs interest coverage ⁶

Column headers

Row headers

Objective	2019	2018
	\$ 15,732	\$ 13,785
	\$ 5,533	\$ 5,091
	\$ 660	\$ 582
2.00 – 2.50 ⁴	2.84	2.71
	4.3	4.8
	8.4	8.8

1 Net debt is calculated as follows:

As at March 31

Long-term debt
Debt issuance costs netted against long-term debt
Derivative (assets) liabilities, net
Accumulated other comprehensive income amounts arising from financial instruments used to manage interest rate and currency risks associated with U.S. dollar-denominated long-term debt – excluding tax effects
Cash and temporary investments, net
Short-term borrowings
Net debt

Note	2019	2018
26	\$ 15,775	\$ 13,990
	90	75
	41	59
	(86)	(24)
	(588)	(415)
22	500	100
	\$ 15,732	\$ 13,785

2 EBITDA – excluding restructuring and other costs is calculated as follows:

Add
Three-month period ended March 31, 2019
Year ended December 31, 2018
Deduct
Three-month period ended March 31, 2018
EBITDA – excluding restructuring and other costs

EBITDA (Note 5)	Restructuring and other costs (Note 16)	EBITDA – excluding restructuring and other costs
\$ 1,379	\$ 36	\$ 1,415
5,104	317	5,421
(1,269)	(34)	(1,303)
\$ 5,214	\$ 319	\$ 5,533

Table Source:

https://assets.ctfassets.net/rz9m1rynx8pv/2x3p5ompzZyrRtAHw4M3XB/be648275661795139cabcee29a730630/TELUS_Q1_2019_quarterly_report.pdf



How to Score a Table

- Rule-out patterns
 - Rule out charts, lists, signature blocks etc.
- Aggregated column / row score
 - [KD01] Aggregate the similarities that led to the table's column fragments
- Dynamic programming score
 - [H99] $\text{Score}(T) = \max \{ \text{Score}(T - \text{line}) + \text{Merit}(\text{line}) \}$
 - Score the best split into 2 sub-tables
- Probability of being a table (given the features)
 - [W04] Partition page into blocks labeled “table” and “plain text”
 - Compute label probability for block + **neighboring blocks**
- A scoring neural network on top of CNN [G17, S18b]



[H99] [J. Hu et al. “Medium-Independent Table Detection”, SPIE Doc. Recog. & Retr. ‘99](#)

[KD01] [T. Kieninger and A. Dengel. “Applying the T-Recs Table Recognition System to the Business Letter Domain”, ICDAR ‘01](#)

[W04] [Y. Wang et al. “Table Structure Understanding and Its Performance Evaluation”, Pattern Recog. ‘04](#)

[G17] [A. Gilani et al. “Table Detection using Deep Learning”, ICDAR ‘17](#)

[S18b] [S. A. Siddiqui et al. “DeCNT: Deep Deformable CNN for Table Detection”, IEEE Acc. ‘18](#)

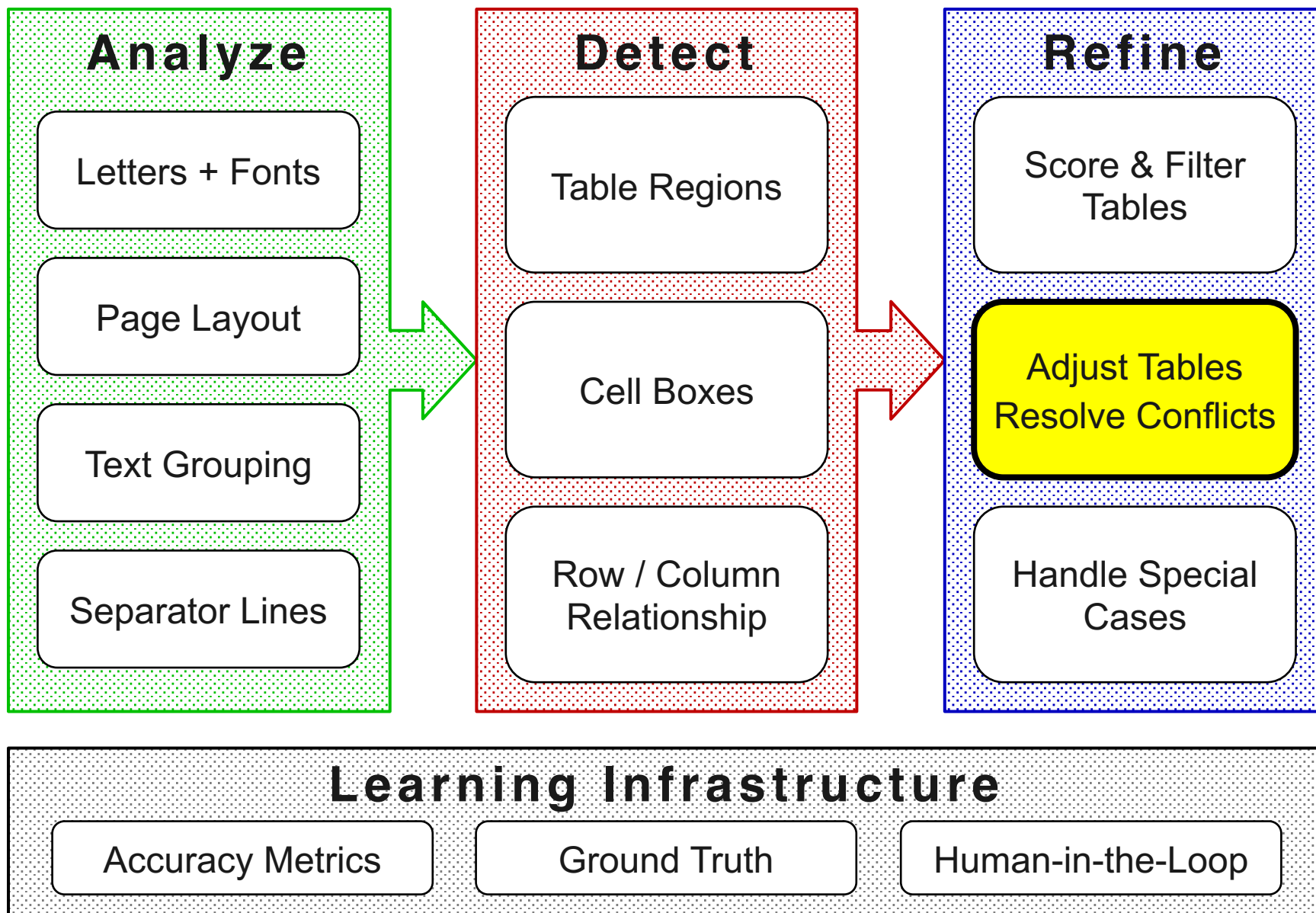


Features for Table Scoring

- Columns and rows:
 - Number, span / extent, alignment, font / content similarity
- Ruled and white-space separators:
 - Number, span / extent, width of their margins
 - If they match, reach (*good*) or cross (*bad*) table borders
- Inside vs. outside table:
 - Border crossing ruled lines, aligned blocks, or highly similar text
 - The two sides have matching structure
- Cell structure:
 - Oversized cells, misaligned pairs of cells, “runs” of empty cells
- Content:
 - Numerics, repeated words; customizable keywords
 - Domain-specific “expectations,” e.g. header dictionary [D11]
- CNN-generated features



Common Sub-Tasks in Table Extraction



Why Adjust Tables?

- Leverage table features and score
 - Specify how a well-formed vs. mal-formed table looks like
- Use a transparent, explainable method
 - If detection is a “black box”, adjustment uses explainable rules & features
- Correct errors quickly
 - Bypass the need for extra ground-truth data, retraining
- Customize to address specific concerns
 - Add custom features, rules, and constraints



[W04] [Y. Wang et al. “Table Structure Understanding and Its Performance Evaluation”, Pattern Recog. ‘04](#)
[HB07] [T. Hassan and R. Baumgartner. “Table Recognition and Understanding from PDF Files”, ICDAR ‘07](#)
[SS10] [F. Shafait and R. Smith. “Table Detection in Heterogeneous Documents”, DAS ‘10](#)
[D11] [F. Deckert et al. “Table Content Understanding in smartFIX”, ICDAR ‘11](#)
[G17] [A. Gilani et al. “Table Detection using Deep Learning”, ICDAR ‘17](#)
[S18b] [S. A. Siddiqui et al. “DeCNT: Deep Deformable CNN for Table Detection”, IEEE Acc. ‘18](#)

How to Adjust Candidate Tables

- **Merge table** with an adjacent table or text-block [W04] [SS10]
- **Adjust table border** – add or drop rows or columns [HB07] [D11]
- **Split one table into two**, possibly with plain text between
- **Re-compute table region** by neural network regression [G17] [S18b]
- **Choose best-scoring** border (or structure) out of a range of options
- Iterate adjustment → **traverse a search tree** of candidate tables



[W04] [Y. Wang et al. "Table Structure Understanding and Its Performance Evaluation", Pattern Recog. '04](#)
[HB07] [T. Hassan and R. Baumgartner. "Table Recognition and Understanding from PDF Files", ICDAR '07](#)
[SS10] [F. Shafait and R. Smith. "Table Detection in Heterogeneous Documents", DAS '10](#)
[D11] [F. Deckert et al. "Table Content Understanding in smartFIX", ICDAR '11](#)
[G17] [A. Gilani et al. "Table Detection using Deep Learning", ICDAR '17](#)
[S18b] [S. A. Siddiqui et al. "DeCNT: Deep Deformable CNN for Table Detection", IEEE Acc. '18](#)

Select Best Tables for Output

What if candidate tables overlap each other?

- [H99] uses **Dynamic Programming**:

- Only for top and bottom line-positions: $[i, j]$
- Score disjoint unions of tables:

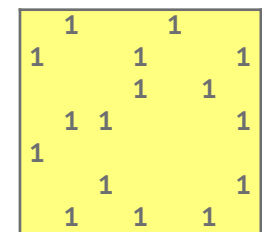
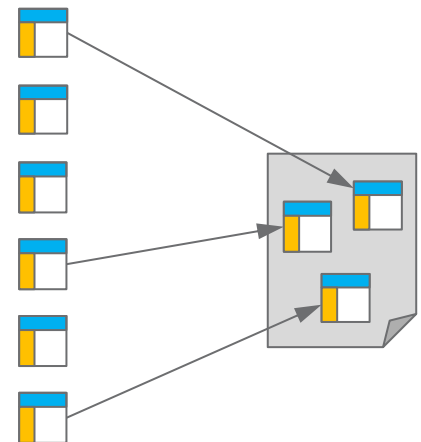
$$score[i, j] = \max \begin{cases} tab[i, j] \\ \max_{i \leq k < j} \{score[i, k] + score[k + 1, j]\} \end{cases}$$

- CNN-based object detection systems:

- **Greedy Approach**: Pick the top-scoring region, repeat
- PROBLEM: Lower-scoring table may have a high-scoring sub-table

- **Maximum Weighted Independent Set**

- Nodes = tables, edges = conflicts, weights = table scores
- NP-hard even for 2-dim rectangles [RN95], but can be solved efficiently in real-life cases



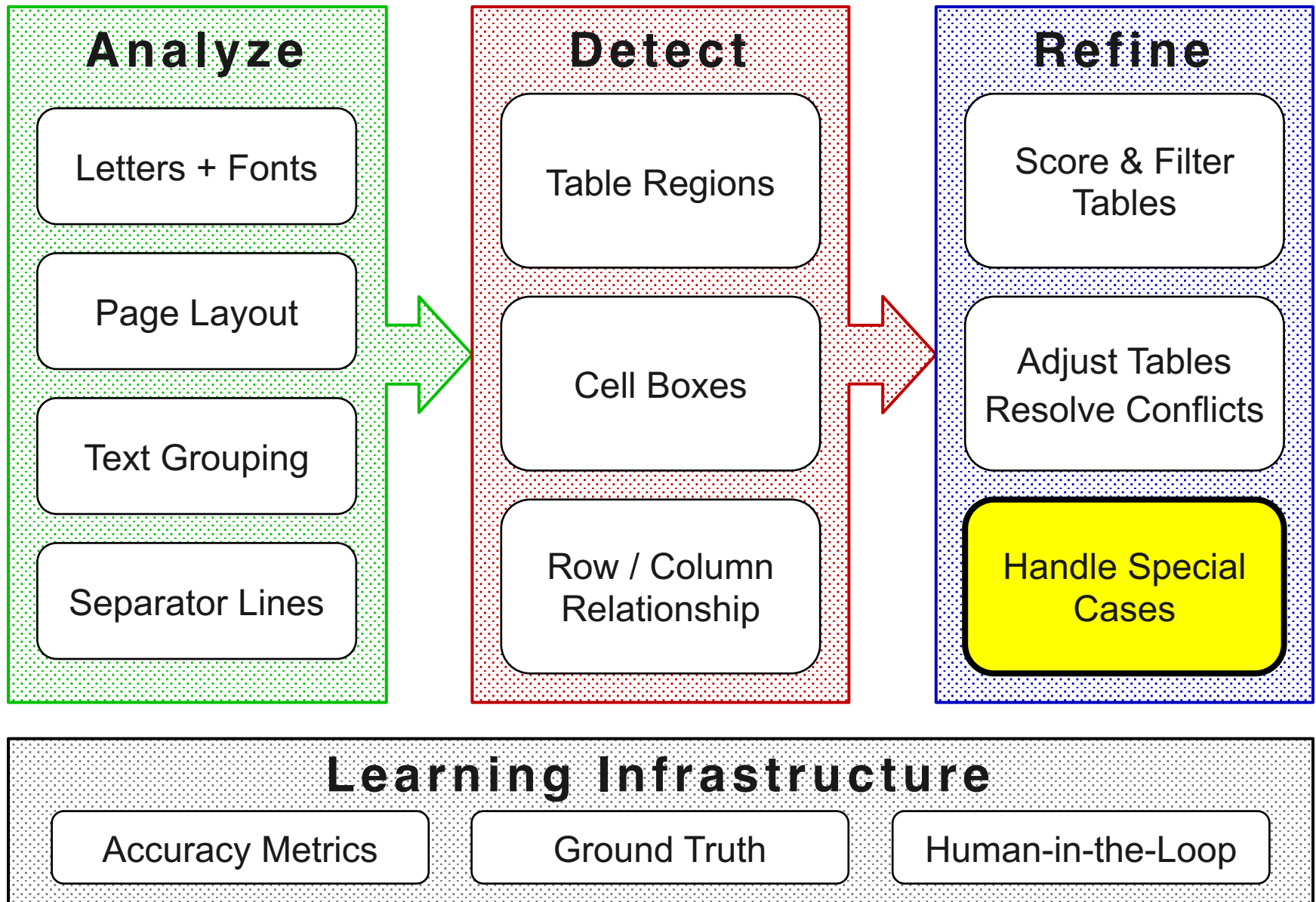
Conflict = Table
Overlap



[H99] J. Hu et al. "Medium-Independent Table Detection", SPIE Doc. Recog. & Retr. '99

[RN95] C.S. Rim and K. Nakajima. "On Rectangle Intersection and Overlap Graphs", IEEE Trans. on Circuits & Systems I, 42(9), 1995

Common Sub-Tasks in Table Extraction



Handle Customer Specific Rules and Forms

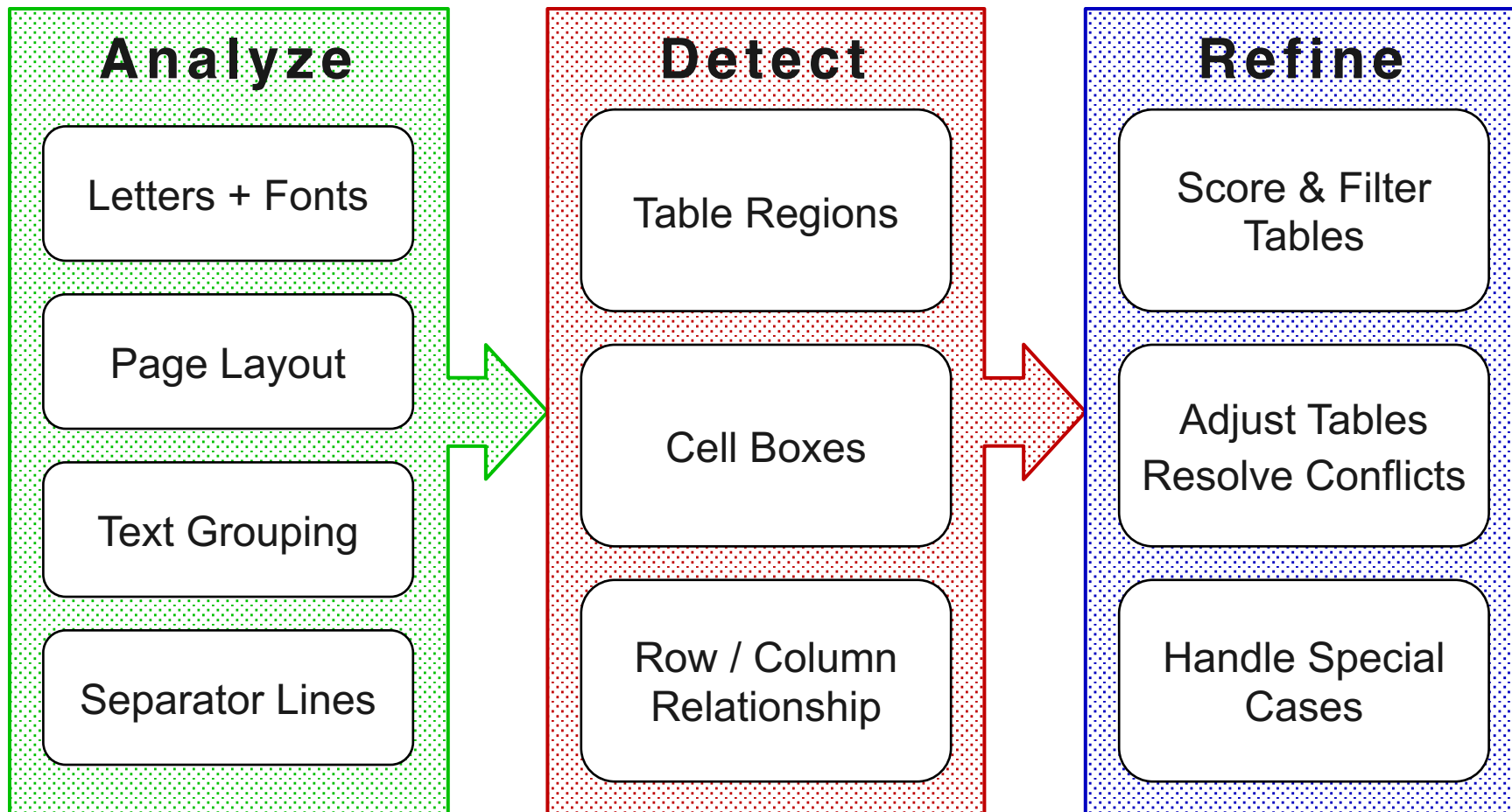
- Customers need ~100% accuracy on specific tables
 - Invoices & financial reports
 - Healthcare forms
 - Contracts, insurance and legal documents
- Customers may only label a few examples
 - Not enough to learn a new ML / DL model
 - Learning a new model may jeopardize older correct results
- Customers want to see how decisions are made
 - Explain how a certain table is handled
 - Provide a guarantee for a (narrow) class of tables
- **Solution:** Refine results with a human readable ruleset



[K01] [B. Klein et al. "Three Approaches to Industrial Table Spotting", ICDAR '01](#)

[D11] [F. Deckert et al. "Table Content Understanding in smartFIX", ICDAR '11](#)

Common Sub-Tasks in Table Extraction



Learning Infrastructure

Accuracy Metrics

Ground Truth

Human-in-the-Loop

Learning from Data: Challenges

▪ Accuracy Metrics

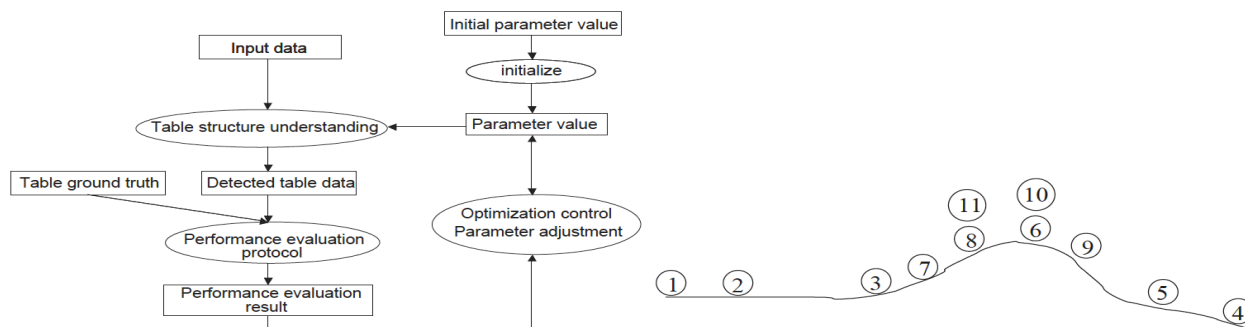
- Exact match of table region or structure is too inflexible
- Partial match: Text? Area? Cell relationship? Functional?

▪ Ground Truth Labeling

- Very time consuming, requires sophisticated UI tools
- Humans disagree on what's correct

▪ Optimization (pre- deep learning)

- Lots of discrete, non-differentiable steps
- **Learn sub-tasks**, e.g. row labeling with CRF / SVM
- [W04] Global parameter learning:



Accuracy Metrics

ICDAR 2013 Competition Metrics

Table Boundary

- Purity & Completeness
- Character level recall, precision and F1

level of experience has been defined, considering the number of responses obtained in the study. These weights, as presented in the table below, have also been applied to the results, producing the weighted averages.

GT Table A

	0-4 years	5-7 years	8-10 years	11-15 years	> 15 years	TOTAL
Number of responses	1,528	1,058	729	787	2,008	6,110
Weights	25,01%	17,32%	11,93%	12,88%	32,86%	

Foreign objects

Table 6 – Weights applied per level of experience

In a similar way, weights per level of experience and gender have been calculated and applied. These weights are presented in the table below.

GT Table B

	0-4 years	5-7 years	8-10 years	11-15 years	> 15 years	TOTAL
Number of responses- Female	695	400	260	260	451	2,066
Weights	33,64%	19,36%	12,58%	12,58%	21,83%	
Number of responses- Male	859	683	483	537	1562	4124
Weights	20,83%	16,56%	11,71%	13,02%	37,88%	

Detected (merged) table region

Table 7 – Weights applied per level of experience and gender

Table Structure

- Recall and Precision of Cell Adjacency Relations

Description	Initial balance	Increase	Decrease	Final balance
Accrued income	1 669	0	1 269	400
Deferred income	26 676	0	26 079	597
Accrued expenses	49 734	0	14 467	35 267

(a) Original table as in ground truth

Description	Initial balance	Increase	Decrease	Final balance
Accrued income	1 669	0	1 269	400
Deferred income	26 676	0	26 079	597
Accrued expenses	49 734	0	14 467	35 267

(b) Incorrectly recognized cell structure with split column

- Correct adjacency relations □ Incorrect adjacency relations

$$\text{Recall} = \frac{\text{correct adjacency relations}}{\text{total adjacency relations}} = \frac{24}{31} = 77.4\%$$

$$\text{Precision} = \frac{\text{correct adjacency relations}}{\text{detected adjacency relations}} = \frac{24}{28} = 85.7\%$$



Accuracy Metrics

ICDAR 2019 Competition Metrics

Two Document types, modern and archival, in image format only.

Table Boundary

Intersection over union (IOU) at varying thresholds (0.6,0.7,0.8,0.9) and weighted average comparing ground truth and predicted table bounding boxes

Table Structure

Adjacency relationship like ICDAR 2013 but cell accuracy is based on IOU of cell bounding boxes instead of text content.

Verfilmungsstelle	Bestandsbezeichnung	Archivaleinheiten	Filmsignatur	Aufnahme-Nr.
BLHA	Theodor-Fontane-Archiv Handschriften	Aufzeichnungen, Dokumente G 2.3 Haushaltsbuch 1864-65	19FA1200200006	8464



Accuracy Metrics

ICDAR 2020 Competition Metrics

Task A

Document layout recognition

- Dataset: [PubLayNet](#)
- Task: Identifying the position and category of document layout elements, including title, text, figure, table, and list.
- Metric: [Mean Average Precision @ IoU](#)
- Important dates:
 - 20th July, 2020: Open for submission
 - 31st March, 2021: Submission close
 - 1st May, 2021: Announcement of winning team

Task B

Table Structure Recognition

- Dataset: [PubTabNet](#)
- Task: Converting table images into HTML code
- Metric: Tree-edit-distance-based similarity ([TEDS](#))
- Important dates:
 - 20th July, 2020: Open for test submission
 - 28th March, 2021: Open for final evaluation submission
 - 31st March, 2021: Submission close
 - 1st May, 2021: Announcement of winning team



Accuracy Metrics

Functional Metrics

- Measure **what actually matters** downstream
- Capture accuracy of access paths to each cell
- Need **header annotation** as well as cell structure

		Turnover (\$bn)		
		2008	2009	2010
AA	American Airlines	17.5	18.1	17.2
AF	Air France	11.6	10.8	11.9
KL	KLM Royal Dutch Airlines	8.3	9.5	9.4
LH	Lufthansa	12.8	14.1	13.8
NA	New Airline		2.1	2.4

Functional representation:

```
[AA],[Turnover ($bn).2008] → [17.5],
[American Airlines],[Turnover ($bn).2008] → [17.5],
[AA],[Turnover ($bn).2009] → [18.1],
[American Airlines],[Turnover ($bn).2009] → [18.1],
...,
[NA],[Turnover ($bn).2008] → [],
```



Ground Truth Datasets

Complete Datasets with table boundary, cell boundary, and cell structure:

- ICDAR-2013 competition (PDF Format) [G12]
- ICDAR-2019 competition (Image Format) [G19]
- SciTSR 2019 (Generated from LaTeX files)[C09]
- PubXNet 2020 (PDF Format) [Z20a]
- FinTabNet 2020 (PDF Format) [Z20b]

Incomplete Datasets

- Table-bank (table boundary information and cell structure only)[L20]
- PubLayNet (table boundary information only)[Z19]
- PubTabNet (Cell structure information only)[Z20b]
- PDF-Trex (Financial Table dataset without ground truth Labels)[O09]
- Marmot (Only ground truth for table boundary, cells inaccessible)
- UNLV , UW-3 (Table structure and boundary annotations for scanned documents)



[C09] [Chi et al. "Complicated Table Structure Recognition" arXiv 2019](#)

[OR09] [E. Oro and M. Ruffolo. "PDF-TREX: An Approach for Recognizing and Extracting Tables from PDF Documents", ICDAR '09](#)

[G12] [Göbel et al. "A Methodology for Evaluating Algorithms for Table Understanding in PDF Documents". DocEng '12](#)

[L20] [Li et al. "TableBank: Table Benchmark for Image-based Table Detection and Recognition". LREC 2020](#)

[Z20a] [Zheng et al. Global Table Extractor \(GTE\): A Framework for Joint Table Identification and Cell Structure Recognition Using Visual Context, arXiv 2020](#)

[Z19] [Zhong et al. Publaynet: largest dataset ever for document layout analysis, ICDAR2019](#)

[Z20b] [Zhong et al. Image-based table recognition: data, model, and evaluation, ECCV 2020](#)

[G19] [Gao et al. Icdar 2019 competition on table detection and recognition\(ctdar\), ICDAR2019](#)

Table Annotation

- Labeling ground truth tables & cells is labor-intensive [W04]
- **Manual annotation:** requires
 - Sophisticated user interface tool [FK15] [HL19] [Z20a]
 - Lots of time and human labor
 - Detailed agreement on how to handle ambiguous cases
- **Automated annotation:** requires
 - HTML and PDF versions of the same documents
 - An automated text matching algorithm [Z20a]
 - Manual editing to fix matching errors (much less labor)



[W04] [Y. Wang et al. "Table Structure Understanding and Its Performance Evaluation", Pattern Recog. '04](#)
[FK15] [M. Frey and R. Kern. "Efficient Table Annotation for Digital Articles", D-Lib Mag. '15](#)
[HL19] [J. Hoffswell and Z. Liu. "Interactive Repair of Tables Extracted from PDF Documents on Mobile Devices", CHI '19](#)
[Z20a] [Zheng et al. Global Table Extractor \(GTE\): A Framework for Joint Table Identification and Cell Structure Recognition Using Visual Context, arXiv 2020](#)