Table Extraction via Eye Gaze Tracking

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- Problem motivation: why use eye gaze tracking for table extraction? Why is table extraction important? (can include discussion of how this is more helpful for labeling tables/identifying specific tables)
- Data discovery: both in terms of gaze data and table data (diverse set of data)
 Initial attempts (just eye gaze eg clustering) and realization that supporting CV models might be
- 4. DL table extraction methods

helpful

- 5. Addition of eye gaze layering (including a description of the "type" of fixation you asked participants to do eg. 4 corner vs 2 corner vs center)
- 6. OCR algorithm (including discussion of why tesseract was not sufficient) and reminder of the diversity of tables considered
- 7. Discussion of how this method might be used in practice and how it compares to other methods

Agenda

- Project Motivation and Objective
- Methodology
- Datasets
- Data Exploration and Insights
- Implementation
 - Baseline Solution
 - Advanced Solution
- Conclusion
- ☐ Future Work



Project Motivation

Why is table extraction important?

- Drastically increasing use of tabular data
- Needs for efficient workflow and smooth knowledge sharing throughout the business

 Consider a use

Why bring in eye gaze tracking?

- For documents with multiple tables, current table extraction solutions cannot distinguish which table is of user's interest
- Eye tracker knows where your attention is on







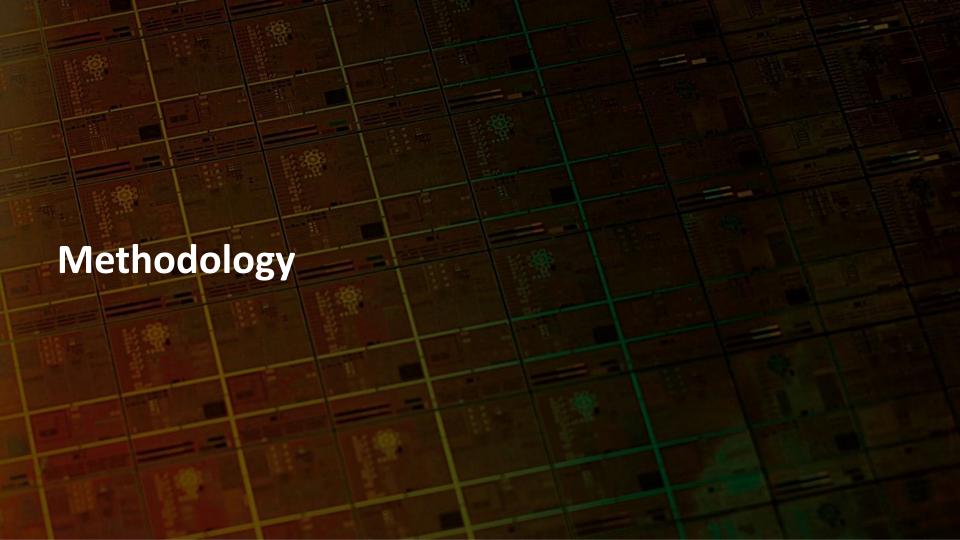
case scenario?



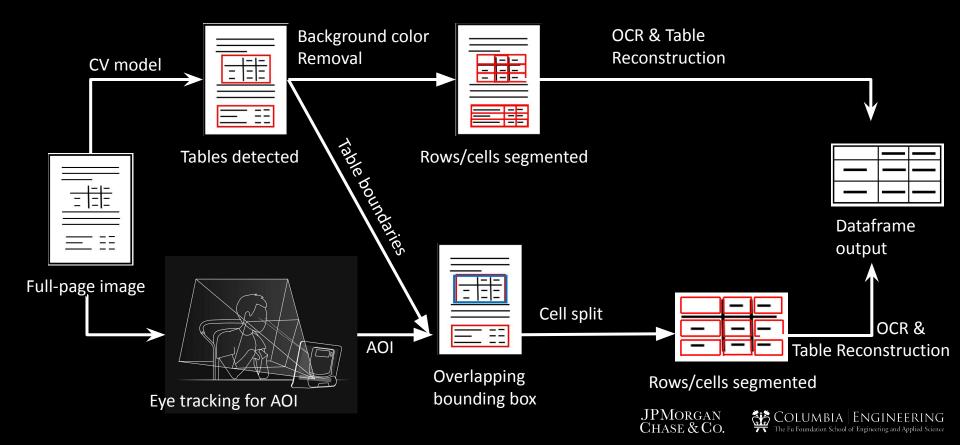
Objective

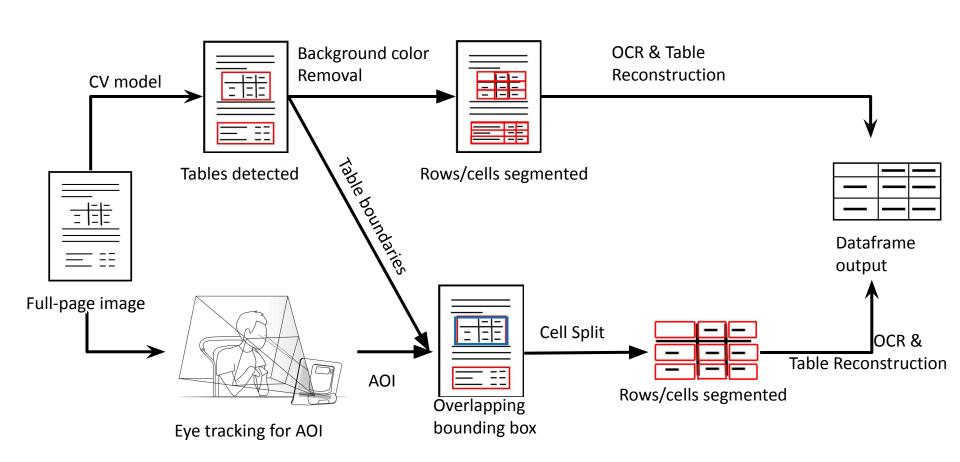
- Leveraging eye gaze technology and Computer Vision (CV) to design a system that automatically detects tables from an image
- Extracting texts from tables with the Optical Character Recognition (OCR) engine Tesseract

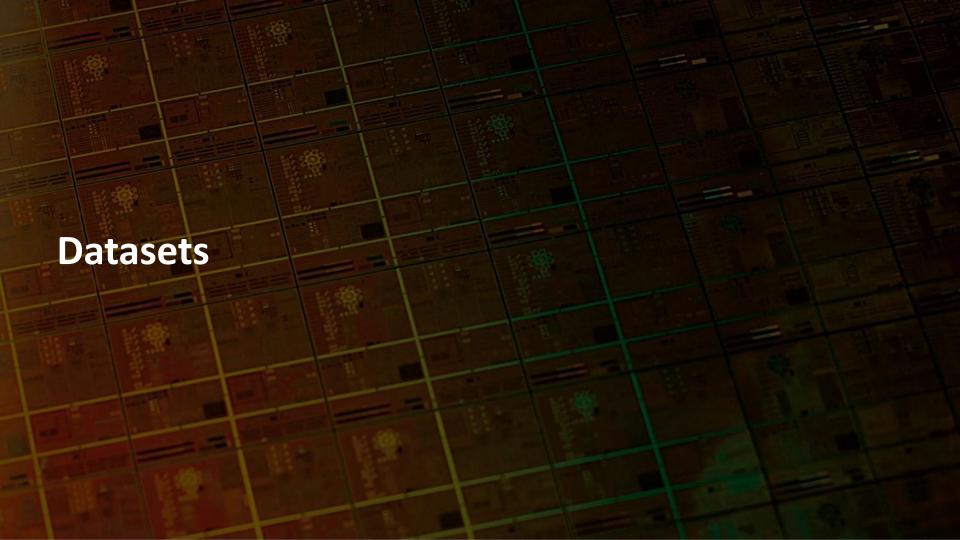




Flow Chart of pygazeTE







Eye Gaze Data





- Designed a webcam-based eye tracking experiment in Python using Gazepoint's eye tracker GP3 and the open-source toolbox PyGaze
- Instructions would lead the participant to calibrate the device, then a number of images would be displayed on the screen for 10 seconds each.
- Eye movements are recorded and used to identify eye movements and areas of interest (AOIs).



Public Data: FinTabNet

• **Source**: IBM's open source dataset

Format: PDF (documents), JSON (annotations)

• **Size**: 16 GB

- Data coverage: about 90k pages of earnings reports from S&P 500 companies with cell annotations
- Description: We used the 2,000 documents images using pdf2img for modeling.
- **Challenges**: borderless, tight rows

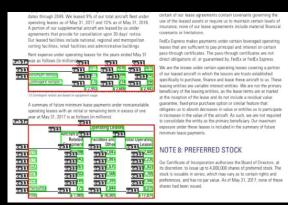
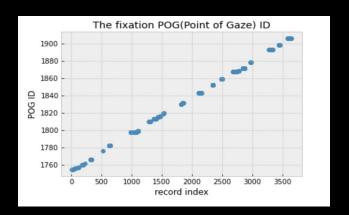


Table structure annotations





Data Exploration and Insights

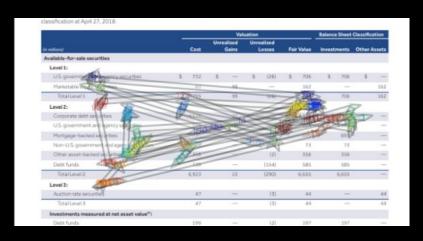


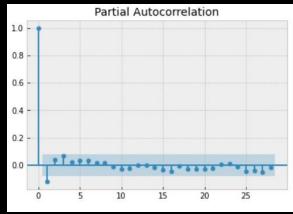
- Critical impact of calibration accuracy
- **Consistency of missing value:** Some data were missed during regular blinking. *The frequency of blinking = total time / counts of blinking*. On average, we found blinks happen every 2.5 seconds and each lasted about 0.3 seconds.





Data Exploration and Insights





- **Difference of reading patterns:** reading habits differ from person to person.
- **Time Series analysis:** eye movements can be potentially predicted with ARIMA(0,1,1) model



Baseline solution: Eye gaze only





April 25, 2014 and April 26, 2013, the credit loss portion of other than temporary impairments on debt securities was \$4 million and \$9 million, respectively. The total reductions for available-for-sale debt securities sold for the fiscal years ended April 24, 2015 and April 25, 2014 were \$4 million and \$5 million, respectively. The total other-than-temporary impairment losses on available-for-sale debt securities for the fiscal years ended April 24, 2015 and April 25, 2014 were not eigraficant The April 24, 2015 balance of available-for-sale debt securities, excluding debt funds which have no single maturity date. upon timing of estimated cash flows, assuming no change in the current interest rate environment. maturitie differ from contractual maturities because the insures of the securities may have the right to prepay obligawithout nac mont nonalties Due in or year through five years As of April 24, 2015 and April 25, 2014, the aggregate carrying amount of equity and other securities without a quoted market price and accounted for using the cost or equity method was \$520 million and \$666 million, respectively. The total carrying value of these investments is reviewed quarterly for changes in circumstance or the occurrence of events that suggest the Company's importance may not be recoverable. The value of cost or equity method investments is not adjusted if there are no identified events or changes in circumstances that may have a material adverse effect on the fair value of the investment Gains and losses realized on trading securities and available-for-sale debt securities are recorded in interest expense, not in the consolidated statements of income. Gains and losses realized on marketable equity securities, cost method, equity method, and other investments are recorded in other expense, not in the consolidated statements of income. In addition, unrealized gains and losses on available for-sale debt securities are recorded in other comprehensive loss in the consolidated statements of comprehe sive income and unrealized gains and osses on trading securities are recorded in interest expense, net in the consolidated statements of income. Gains and losses from the sale of investments are calculated based on the specific 6. Fair Value Measurements

Fixation density maps

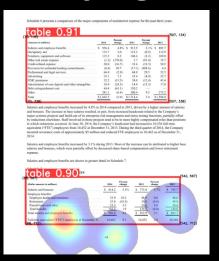
Predicted bounding box

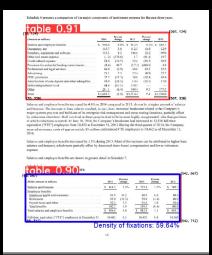
Idea: Crop a bounding box by capturing corners of a table via DBSCAN clustering **Gaze strategy attempts**:

- 1. <u>Four-corner</u>: all corners of the table, 2 seconds each
- 2. <u>Two-corner</u>: only the *upper left* and the *bottom right corners, 5 seconds each*



pygazeTE: Eye gaze + CV + OCR





Idea: Use more precise CV and OCR models to first identify table boundaries and texts, and then use eye fixations to determine the table of interest.

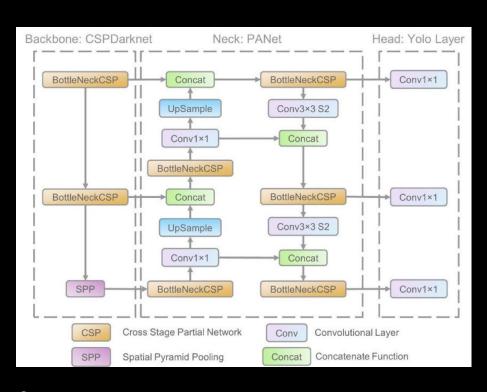
- YOLO-v5: table boundaries prediction
- *Tesseract*: text recognition
- **Pygaze**: AOI prediction

Gaze strategy: <u>Center-focused</u>





Table Detection by Transfer Learning (CV Model)



- Backbone: CSP Darknet
- Neck: PANet
- Head: Yolo layer
- Data are first input to CSP Darknet for feature extraction.
- Then fed to PANet for feature fusion.
- Finally, Yolo Layer outputs detection results (class, score, location, size).

Source:

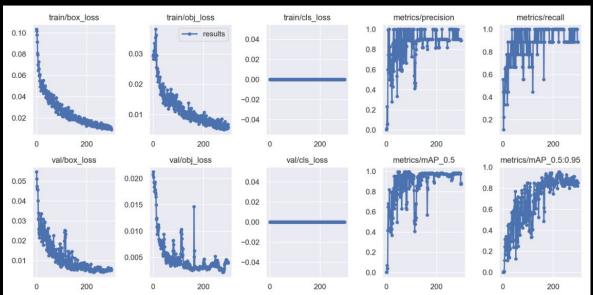


CV Model

1. Train

Trained using **Yolov5x.pt** pretrained weights for 300 epochs, on 80 annotated images and tested on 20 images with the mAP of 0.824.

- As the object category in this experiment is only table, the classification loss is 0.







CV Model

2. Evaluate

Total Loss = Classification Loss + Localization Loss + Confidence Loss

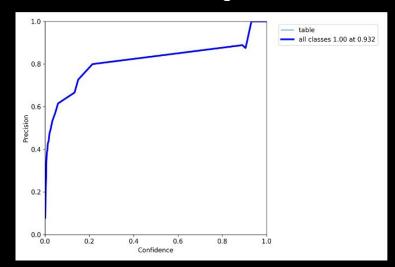
Classification Loss: 0.0

- Localization Loss : 0.005

- Confidence loss : 0.004

The P-Curve shows that the model has a high confidence on detecting a table with high precision

in the test set.





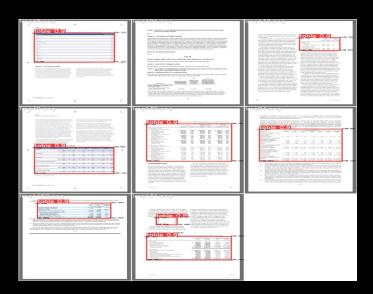


CV Model

3. Output

Given document images as input, the model will:

- detect all tables with confidence scores
- crop each table with its coordinates



		Fiscal Year					
	100	2016	_	2015	-	2014	
(in millions, except per share data) Net sales	s	28,833	s	20,261	s	17,005	
Costs and expenses:							
Cost of products sold		9.142		6,309		4,333	
Research and development expense		2,224		1,640		1,477	
Selling, general, and administrative expense		9,469		6,904		5,847	
Special charges (gains), net		70		(38)		40	
Restructuring charges, net		290		237		78	
Certain litigation charges, net		26		42		776	
Acquisition-related items		283		550		117	
Amortization of intangible assets		1,931		733		349	
Other expense, net		107		118		181	
Operating profit		5,291		3,766		3,813	
Interest income		(431)		(386)		(271	
Interest expense		1,386		666		379	
Interest expense, net		955		280		108	
Income from operations before income taxes	4.336			3,486		3,705	
Provision for income taxes		798		811		640	
Net income	S	3,538	S	2,675	S	3,065	
Basic earnings per share	S	2.51	\$	2.44	S	3.06	
Diluted earnings per share	8	2.48	5	2.41	S	3.02	
Basic weighted average shares outstanding Diluted weighted average shares outstanding		1,409.6 1,425.9		1,095.5		1,002.1	
Cash dividends declared per ordinary share	S	1.52	s	1.22	S	1.12	

0 0.507949 0.336025 0.799682 0.458385





OCR Model: Tesseract

1. Train

Trained using Tesseract with annotated images of 2000 tables, based on English-language pretrained model

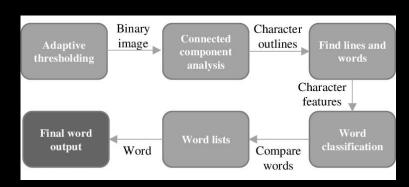
method: single-line page segmentation(psm=7)

· datasize: 12.8k

· input: cropped single-cell images of each table

· output: retrained language model fintabnet full.traineddata





OCR Model

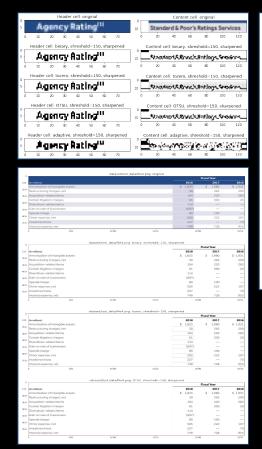
2. Preprocessing

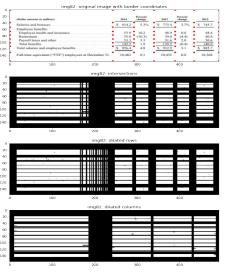
Problems for prediction:

- headers with darker background colors are hard to recognize
- recognizing the whole table is harder than recognizing each cell

Solution:

- background removal
- reconstruct table structure, then separate each cell
- implemented using OpenCV





reconstructing table structure, drawing borders and separating cells

comparisons among background removal methods, for single cell and the entire table



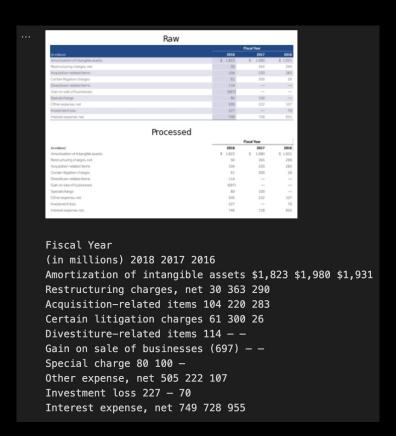


OCR Model: Tesseract

3. Predict

Our OCR predictor supports two modes:

- (1) Table mode: recognize the entire table, output all text with built-in table structure (psm=6 or 12)
 - faster, preserves row-column table structures
- (2) Cell mode: recognize text per cell, then reconstruct table structure (psm=7)
 - more accurate, preserves row structures



OCR Model: Tesseract

4. Evaluate

- Evaluated using 1.2k single-line images of table cells (10% of the entire dataset)
- Metrics:
 - Character Error Rate (CER)
 - Word Error Rate (WER)
 - Accuracy

$$CER = (S+D+I)/N$$
 $WER = (S_w + D_w + I_w)/N_w$
where:
 $S = Number of Substitutions$
 $D = Number of Deletions$
 $I = Number of Insertions$
 $N = Number of characters in reference text$
(aka ground truth)

Mode	Structured text (psm 6)	Unstructured text (psm 12)	Single-line (psm 7)
Train Acc.	-	-	98.4%
Test Acc.	97.0%	97.7%	98.9%



Time Comparison

Average time spent based on 4 images per trial (includes response wait time) :

		Eye gaze	Eye gaze +CV+OCR	
Mean time		4.5 min	3.5 min	
	Model prediction	/	13 sec	
	Initiation	70 sec	70 sec	
Time	Calibration	70 sec	30 sec	
decomposition	Experiment	130 sec	90 sec	
	Preprocessing	0.67 sec	0.06 sec	
	AOI prediction	0.06 sec	0.01 sec	

Note: <u>Initiation</u> time doesn't vary with # images; each <u>calibration</u> attempt takes about 30s; <u>experiment</u> time fluctuates with fixation data validity; other time components are linear varying with # images







Conclusion

- Implemented transfer learning to develop a YOLOv5 object detection model and a Tesseract OCR model to identify tables in a document and recognize texts
- Designed an end-to-end table extraction pipeline to automatically extract the table in AOI based on eye fixations, and returns it in tabular format.
- Built a Python package pygazeTE, wrapping up all functions used in the project for preprocessing, visualizing, and predicting. More information can be found in the repo: https://github.com/ybliu9/pygazeTE







Future Work

- **Eye gaze data quality improvements**: The accuracy of eye gaze data was unstable caused by calibration inaccuracy and trivial posture changes. Improving eye gaze validation would lead to more consistent results.
- Generalization to more diverse tables: Our current solution was not tested on unstructured tables or tables with multi-level headers.
- Deep learning methods for table structure: We used OpenCV's image processing techniques to recognize table structures, but DL solutions would allow training and tuning to provide more flexible and accurate results.



