

OCR and Document Understanding

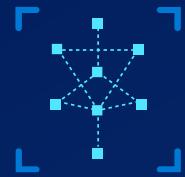


CHA ZHANG

MICROSOFT CLOUD & AI

Azure Cognitive Services

Pre-Trained and Customizable models with your data



Vision



Speech



Language



Decision

Identify and analyze content within images, videos, and digital ink

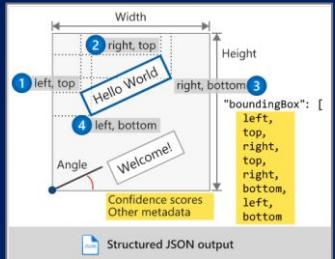
Integrate speech processing into apps and services

Extract meaning from unstructured text

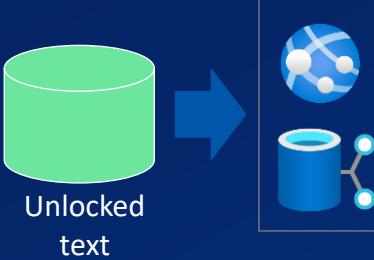
Make smarter decisions faster

As Part of Cognitive Service:

OCR (Read API)

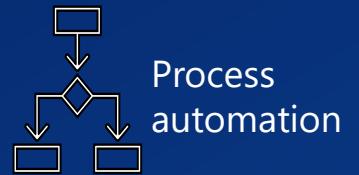


- OCR includes:**
- Pages
 - Text lines
 - Words
 - Locations



Customers and partners add processing to get intelligent insights

ENABLE



Process automation

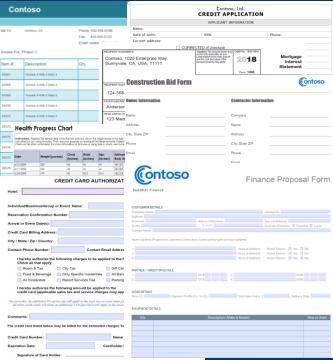
Document Understanding (Form Recognizer APIs)



Layout



Pre-built



Custom

Form Recognizer includes:

- Text extraction
- Document structure
 - Tables
 - Selection marks
- Fields and values
- Other intelligence

ENABLE



Knowledge mining



Industry specific applications



OCR (Read API)

The thing I am concerned about, and so is Mr. Naizenbach, is having something issued so we can convince the public that Oswald is the real assassin. Mr. Kalzenbach thinks that the President might appoint a Presidential Commission of three outstanding citizens to make a determination. I countered with a suggestion that we make an investigative report to the Attorney General with pictures, laboratory work, etc. Then the Attorney General can make the report to the President and the President can decide whether to make it public. I felt this was better because there are several aspects which would complicate our foreign relations. For instance, Oswald made a phone call to the Cuban Embassy in Mexico City which we intercepted. It was only about a visa, however. He also wrote a

The thing I am concerned about, and so is Mr. Naizenbach, is having something issued so we can convince the public that Oswald is the real assassin. Mr. Kalzenbach thinks that the President might appoint a Presidential Commission of three outstanding citizens to make a determination. I countered with a suggestion that we make an investigative report to the Attorney General with pictures, laboratory work, etc. Then the Attorney General can make the report to the President and the President can decide whether to make it public. I felt this was better because there are several aspects which would complicate our foreign relations. For instance, Oswald made a phone call to the Cuban Embassy in Mexico City which we intercepted. It was only about a visa, however. He also wrote a

Challenges for “Universal OCR”

Large scale variability

Large aspect ratio

Cannot be enclosed tightly by axis-aligned rectangles

- e.g., skewed/curved text-lines

Nearby small-size text-lines

- e.g., inter-line space could be less than 2 pixels

Complex/ambiguous layout

Text-like background

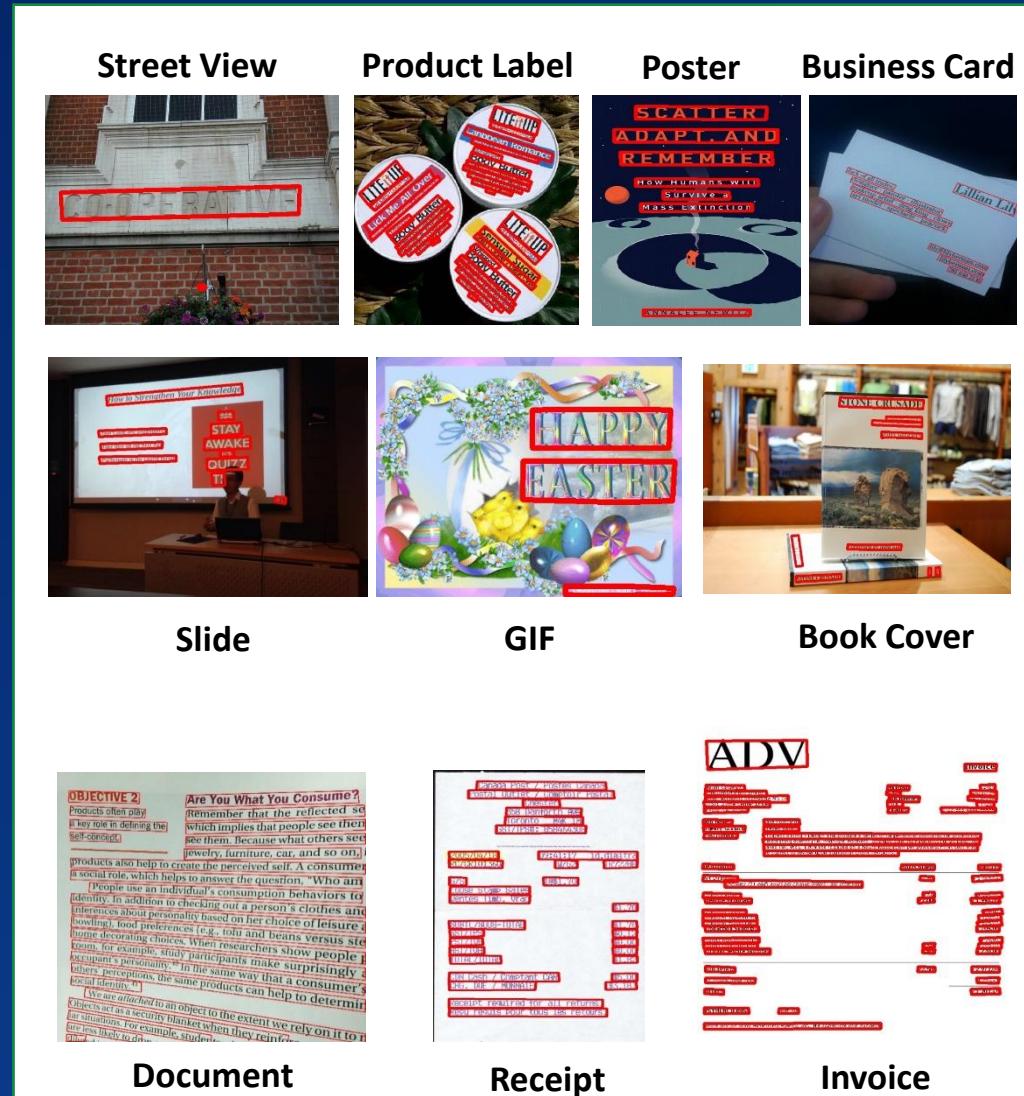
- e.g., fences, bricks, stripes

High localization accuracy is required for text recognition engine

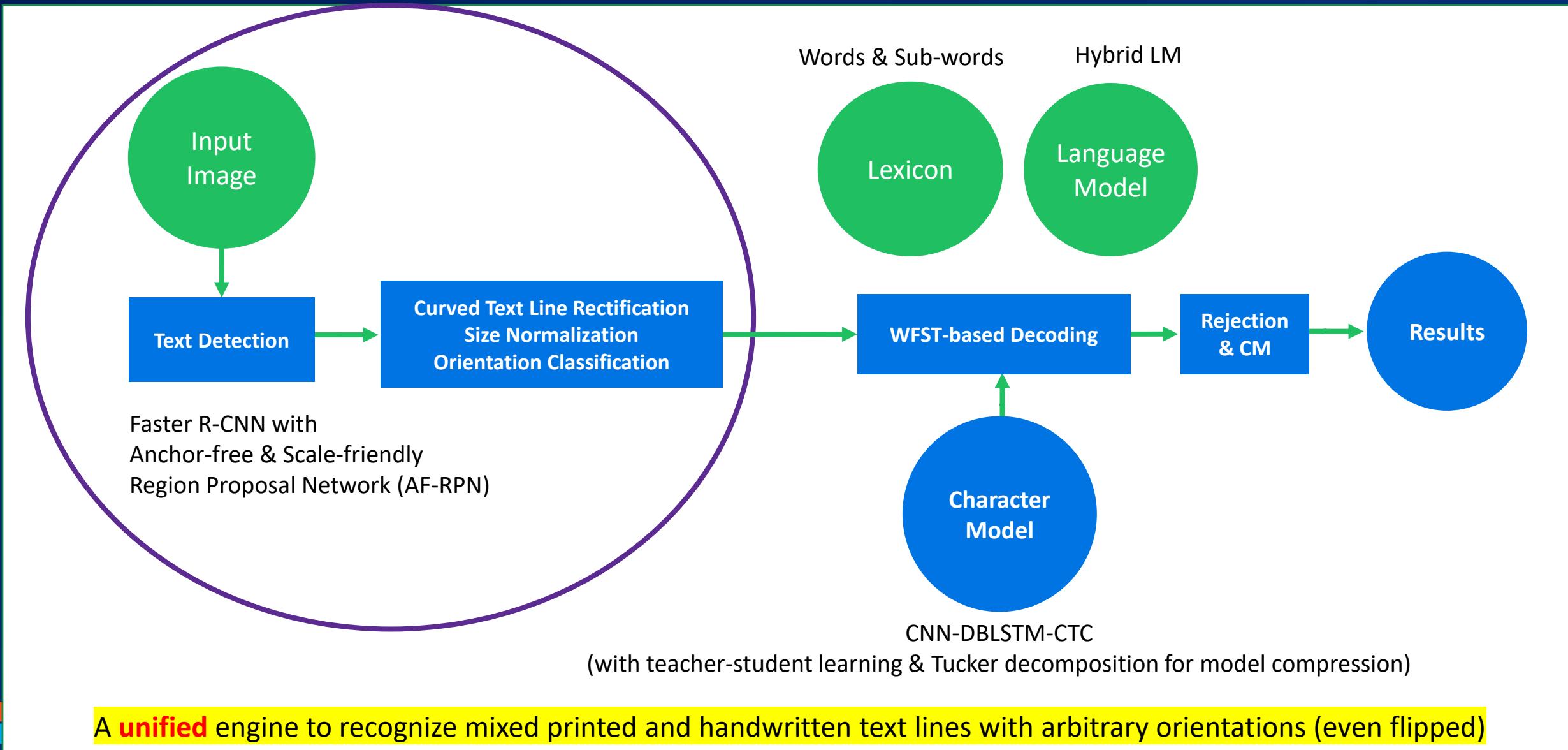
- “ $\text{IOU}>0.5$ ” criterion is far from enough

Resolutions of input images cannot be reduced aggressively

- to avoid excessive small text instances



Read API: Microsoft's New Generation OCR Engine



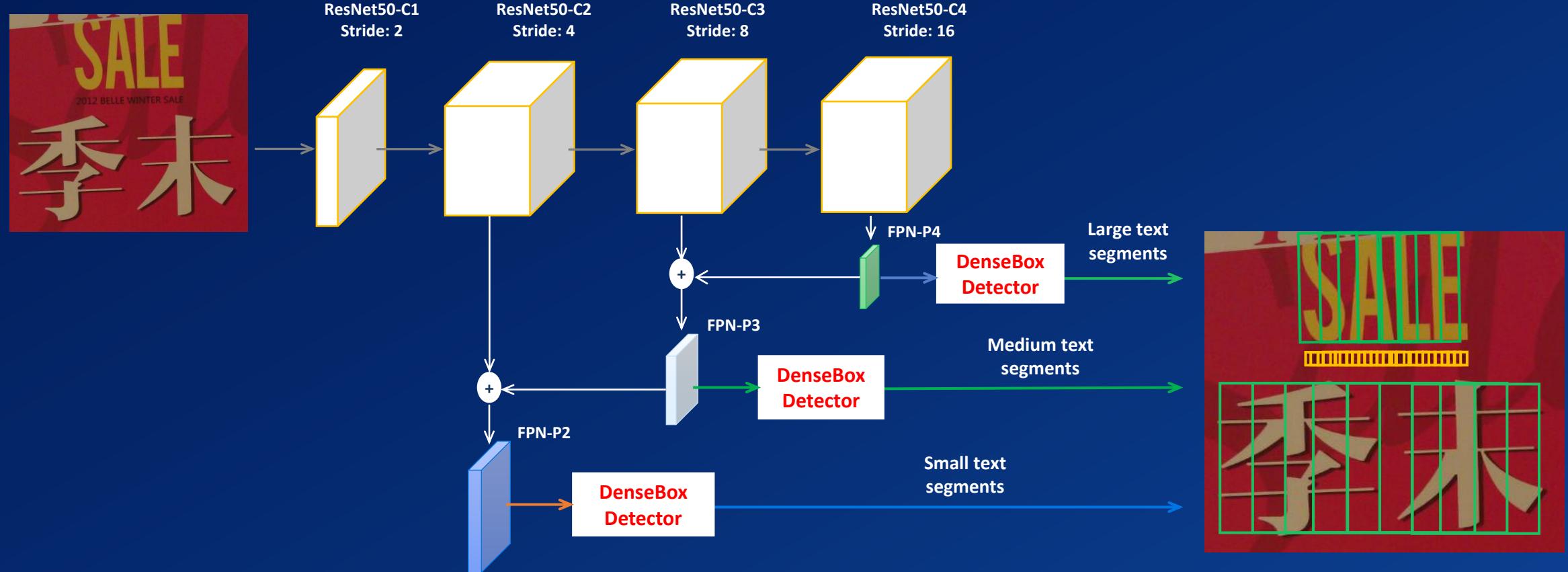
Our Text Detection Approach



[1] JS1-1 “An Anchor-Free Region Proposal Network for Faster R-CNN based Text Detection Approaches,”
Zhuoyao Zhong, Lei Sun, Qiang Huo, ICDAR-2019 oral presentation of the IJDAR paper

[2] PS2-07 “A Relation Network Based Approach to Curved Text Detection,”
Chixiang Ma, Zhuoyao Zhong, Lei Sun, Qiang Huo, ICDAR-2019

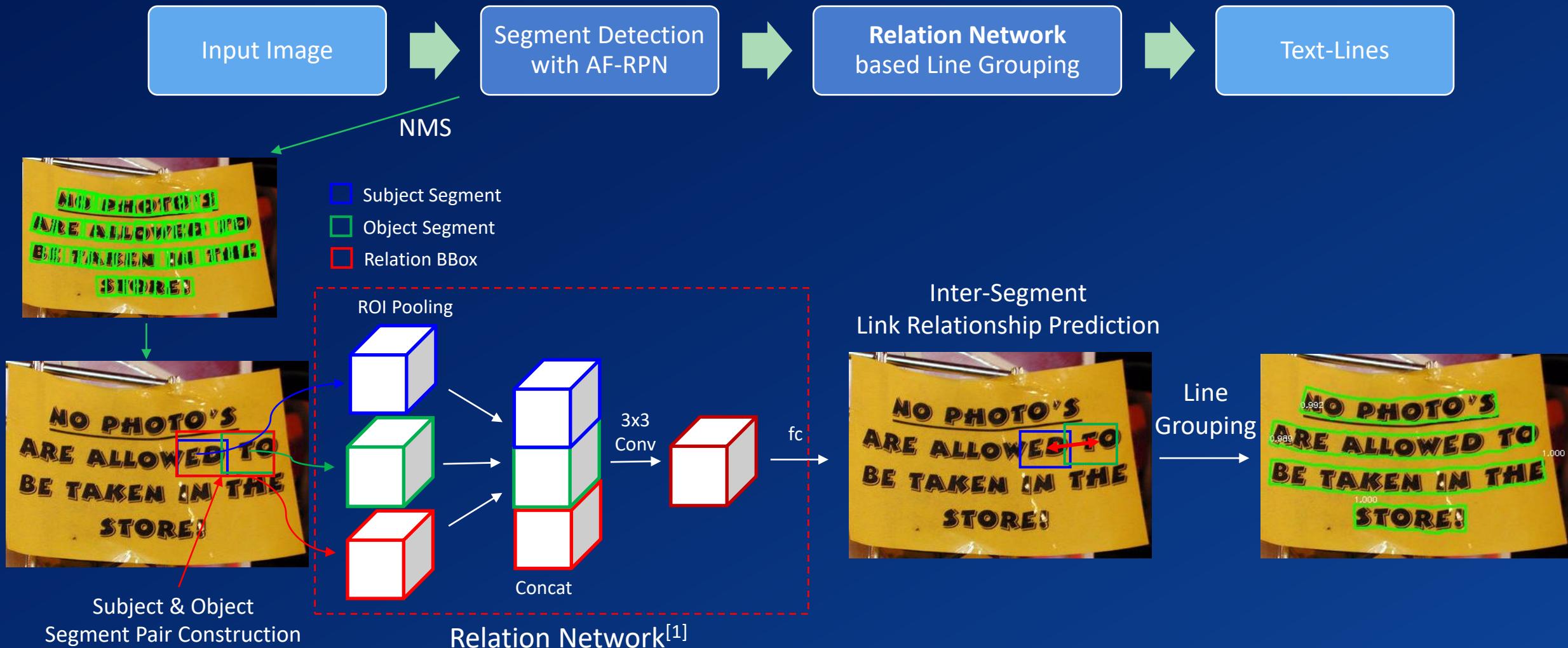
Anchor-Free Region Proposal Network (AF-RPN)



Scale-friendly learning: each DenseBox [1] only detects texts of scales within an appropriate range.

[1] L.-C. Huang, Y. Yang, Y.-F. Deng, and Y.-N. Yu, “Unifying landmark localization with end to end object detection,” arXiv, 2015.

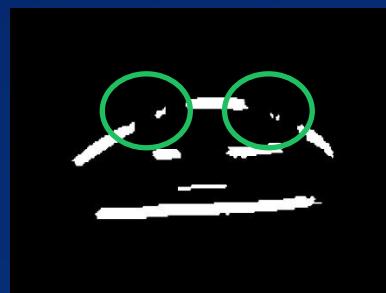
Relation Network based Line Grouping



[1] J. Zhang, M. Elhoseiny, S. Cohen, W. Chang, and A. Elgammal, "Relationship proposal networks," in CVPR, 2017, pp. 5678-5686.

Advantages of Relation Network based Line Grouping

- Leverage the link between the pair of relatively distant segments
 - Able to detect text-lines with large inter-character spaces robustly
- Leverage wider context information to improve link prediction accuracy
 - More robust



Relation Network



SegLink vs. Relation Network



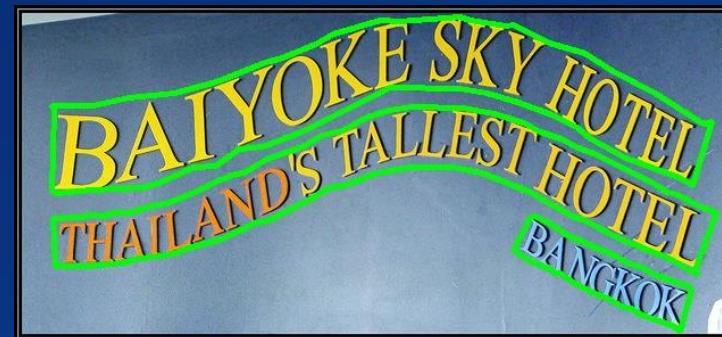
SegLink^[1]



Relation Network

[1] B.-G. Shi, et al., "Detecting oriented text in natural images by linking segments," CVPR, 2017.

Examples on SCUT-CTW1500[1]



[1] Y.-L. Liu, L.-W. Jin, S.-T. Zhang, S. Zhang, "Detecting curve text in the wild: New dataset and new solution," arXiv, 2017.

Challenge of Detecting Small Text in High Resolution Images



Raw high-resolution image

Resize Image



Resized low-resolution image

Text sizes << 12px

Text Detection



Naive solution: use high-resolution image => Very high computation cost

How to detect small texts efficiently in high-resolution images?

Our Solution: Region-wise Adaptive Scaling

Input Image

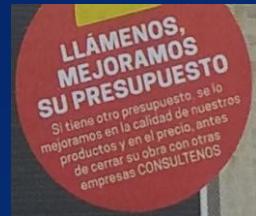
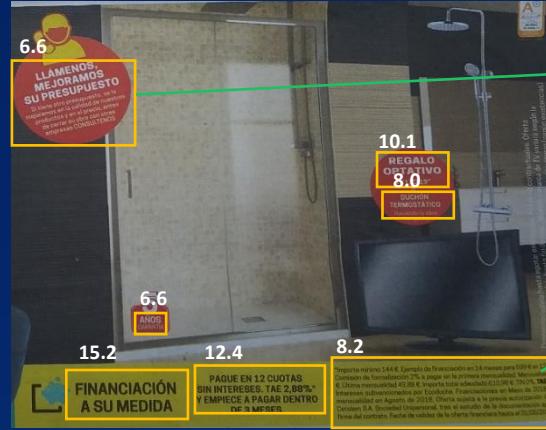
1st Stage Text Block Detection and Scale Estimation

Region-wise Adaptive Scaling

2nd Stage Text Detection

Text-lines

- Coarsely localize text-block regions from a low-resolution input image
- Resize each text-block to make shorter side lengths of contained texts in a working range



Importe mínimo 144 €. Ejemplo de financiación en 14 meses para 629 € en 12 cuotas. Comisión de formalización 2% a pagar en la primera mensualidad. Mensualidad 49,88 €. Última mensualidad 49,88 €. Importe total devuelto 610,96 €. TAE 2,08%. Intereses subvencionados por Ecoducta. Financiaciones en Mayo de 2018. Última mensualidad en Agosto de 2018. Oferta sujetas a la previa autorización de Catiolit S.A. Sociedad Unipersonal, tras el estudio de los documentos que componen el contrato. Fecha de validez de la oferta financiera hasta el 31/08/2018.



Resized low-resolution image

Detected text-blocks with estimated scales

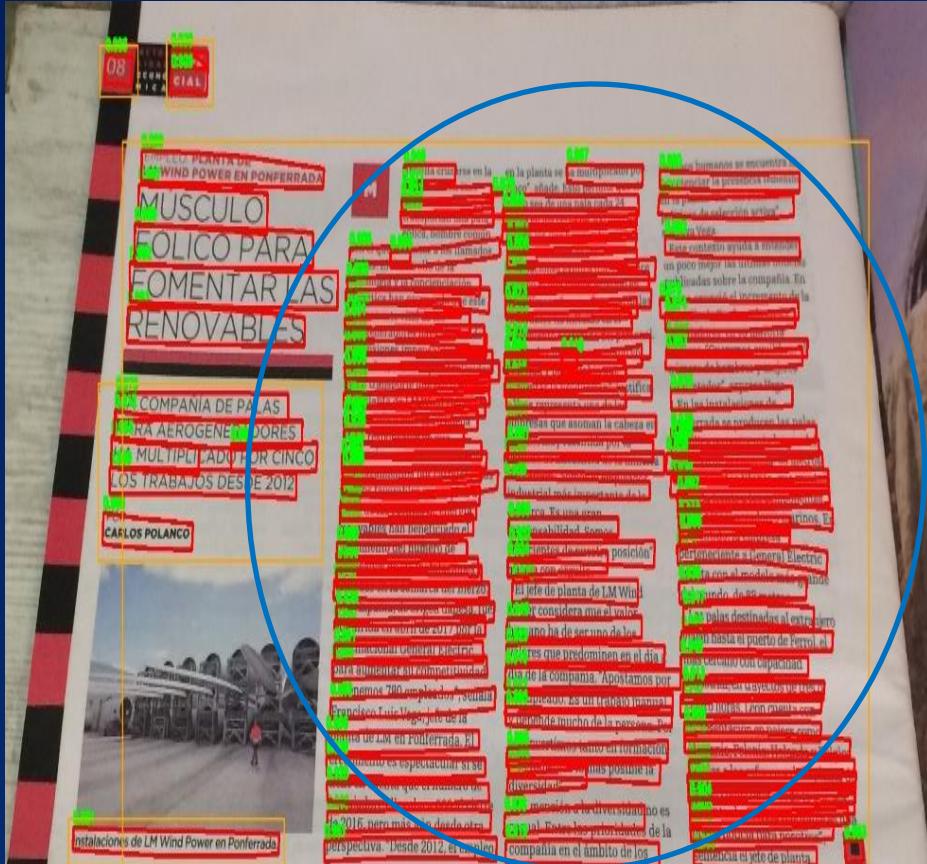
Adaptively re-scaled text-blocks

Detected texts on each Re-scaled Text-block

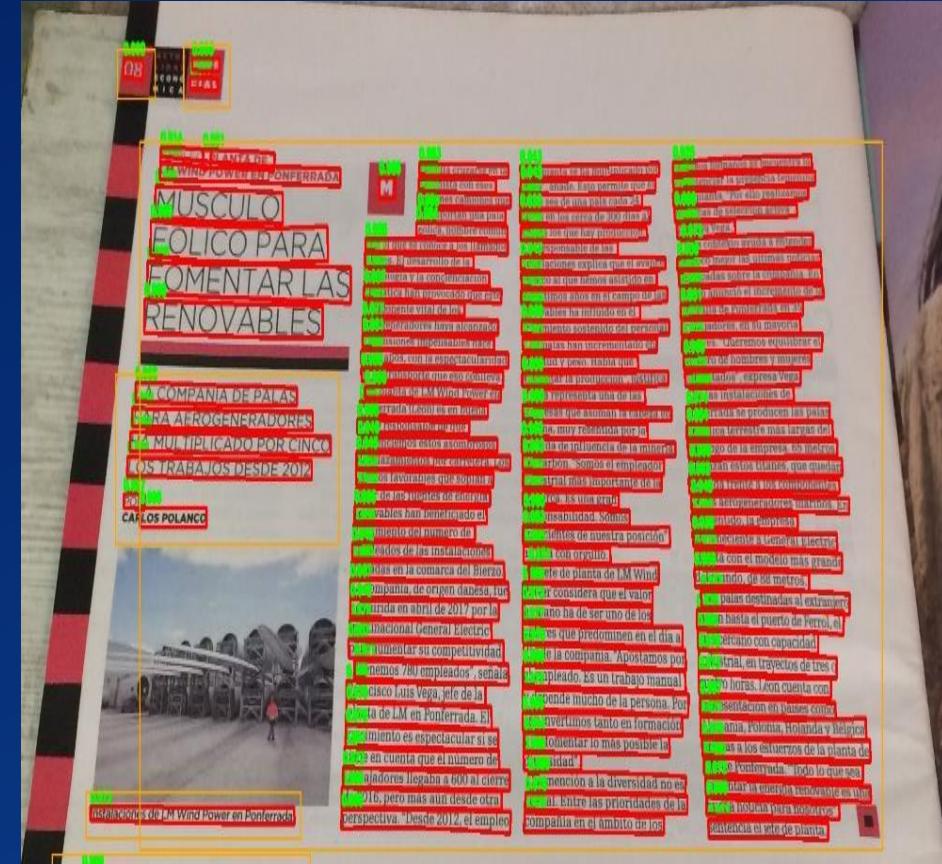
Coarse

Fine

Example

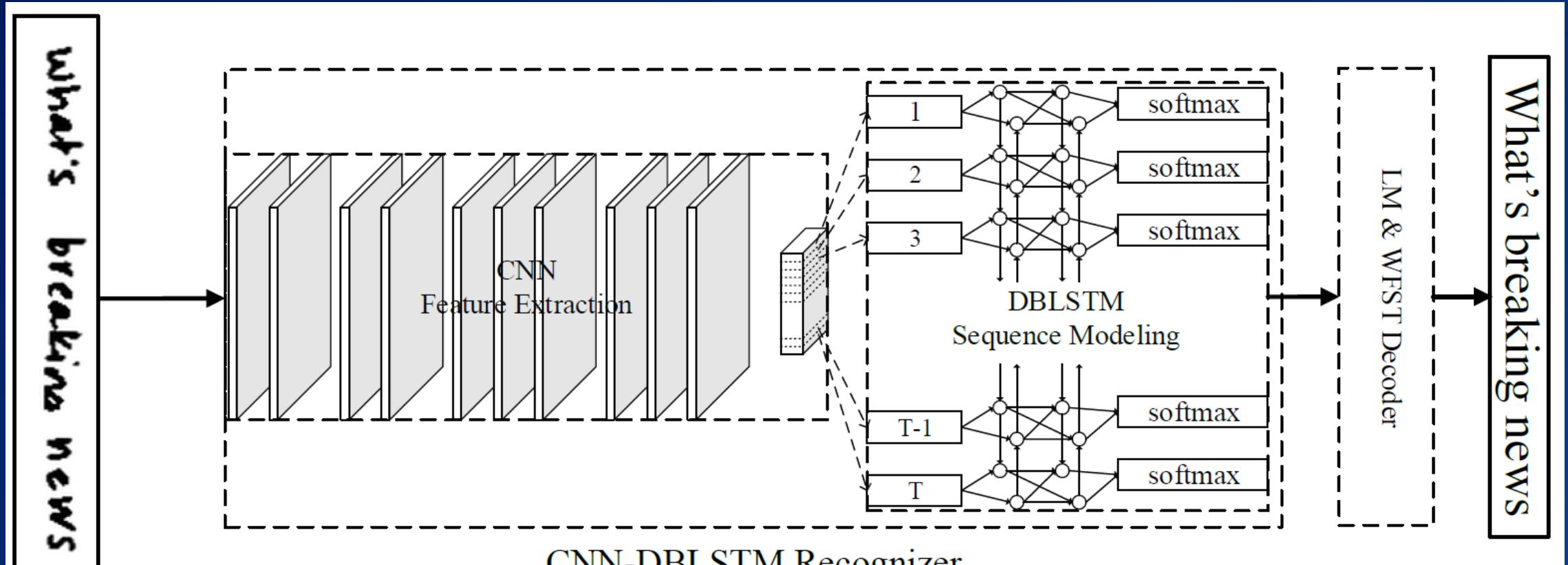


Without adaptive scaling



With region-wise adaptive scaling

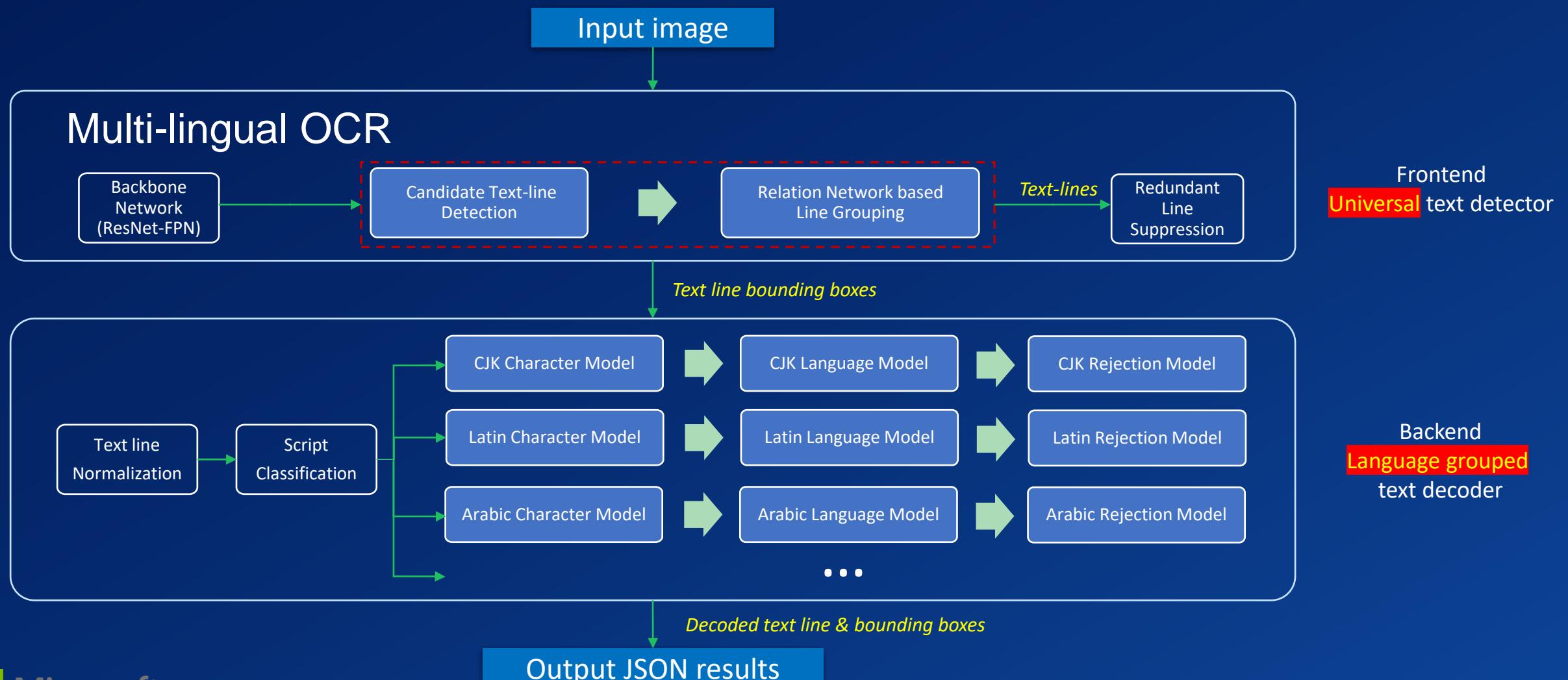
CNN-DBLSTM based Text Decoder



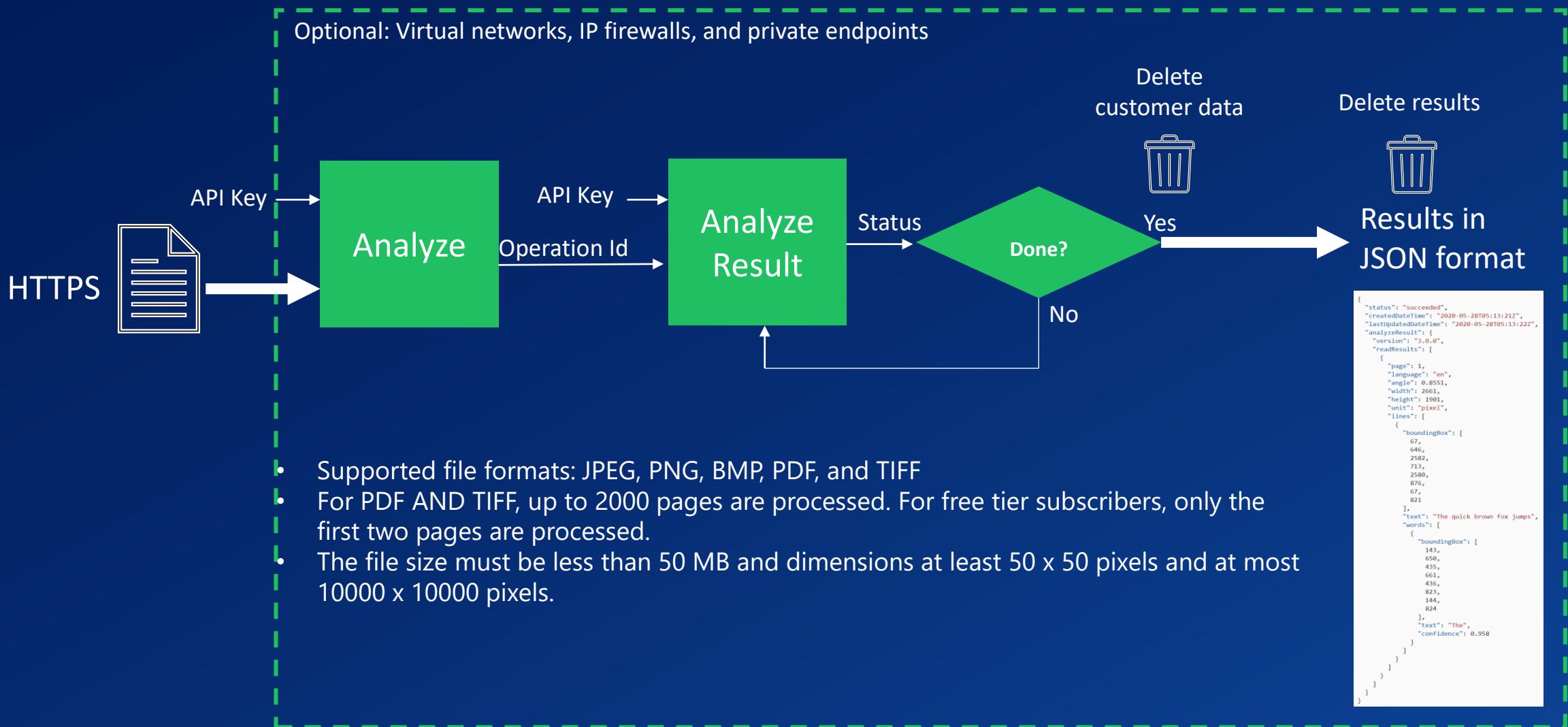
Input

WFST-based
Decoder

Language Expansion



Read API – Available in Cloud and on-Prem



Mixed Languages Comparison (Example)



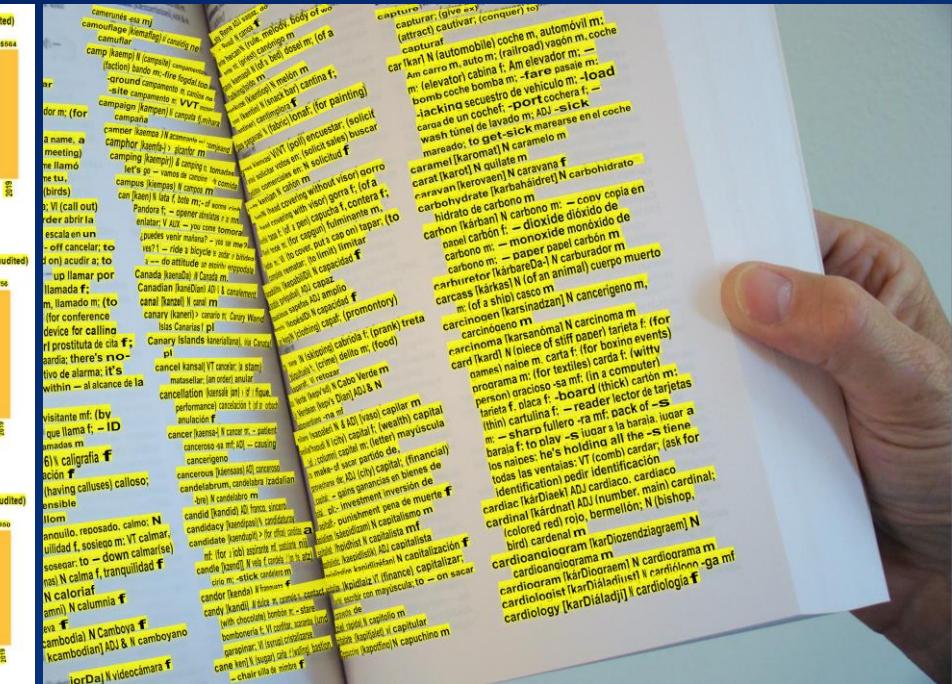
Other OCR auto mode



Microsoft OCR auto mode

Read 3.0+ Examples

1. Text in documents
2. Text in the wild
3. Languages



Images in the Wild



Documents



Documents...

MSCI World Index (USD)

The MSCI World Index captures large and mid cap representation across 23 Developed Markets (DM) countries*. With 1,601 constituents, the index covers approximately 85% of the free float-adjusted market capitalization in each country.

CUMULATIVE INDEX PERFORMANCE (JUL 2005 – JUL 2020)



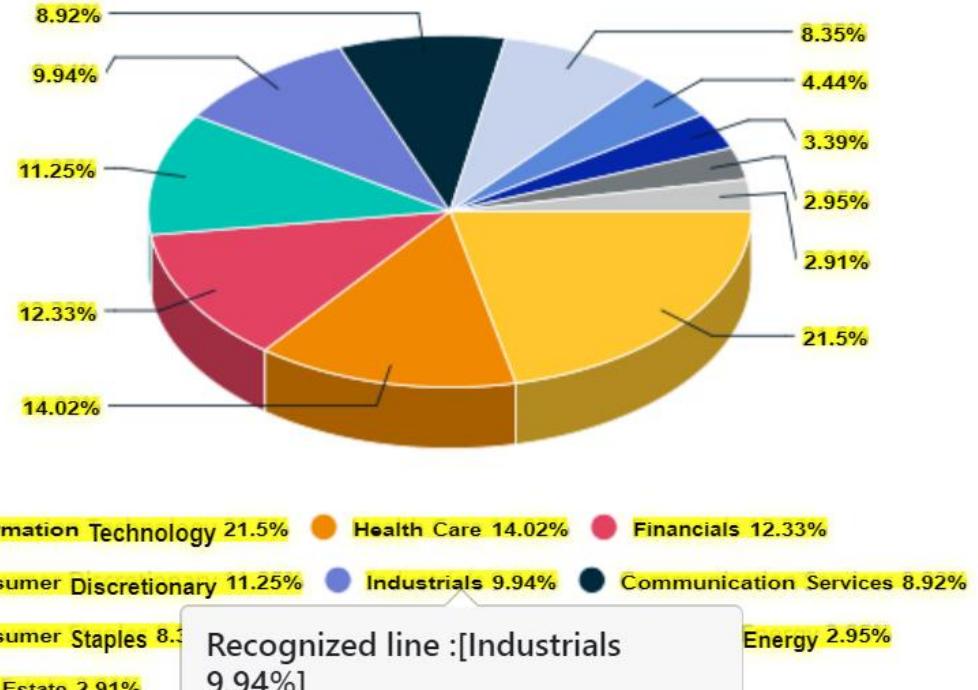
ANNUAL PERFORMANCE (%)

Year	MSCI World	MSCI Emerging Markets	MSCI ACWI
2019	27.67	18.42	26.60
2018	-8.71	-14.67	-9.41
2017	22.40	37.28	23.97
2016	7.81	11.19	7.86
2015	-0.87	-14.92	-2.36
2014	4.94	-2.19	4.16
2013	26.68	-2.60	22.80
2012	15.83	18.22	16.13
2011	-5.54	-18.42	-7.35
2010	11.76	18.88	12.67
2009	29.99	78.51	34.63
2008	-40.71	-53.33	-42.19
2007	9.04	39.42	11.66
2006	20.07	32.14	20.95

INDEX PERFORMANCE — NET RETURNS (%) (JUL 31, 2020)

	ANNUALIZED									FUNDAMENTALS (JUL 31, 2020)			
	1 Mo	3 Mo	1 Yr	YTD	3 Yr	5 Yr	10 Yr	Since Dec 29, 2000	Div Yld (%)	P/E	P/E Fwd	P/BV	
MSCI World	4.78	12.75	7.23	-1.26	7.52	7.52	9.61	5.28	2.08	21.56	20.57	2.55	

SECTOR WEIGHTS

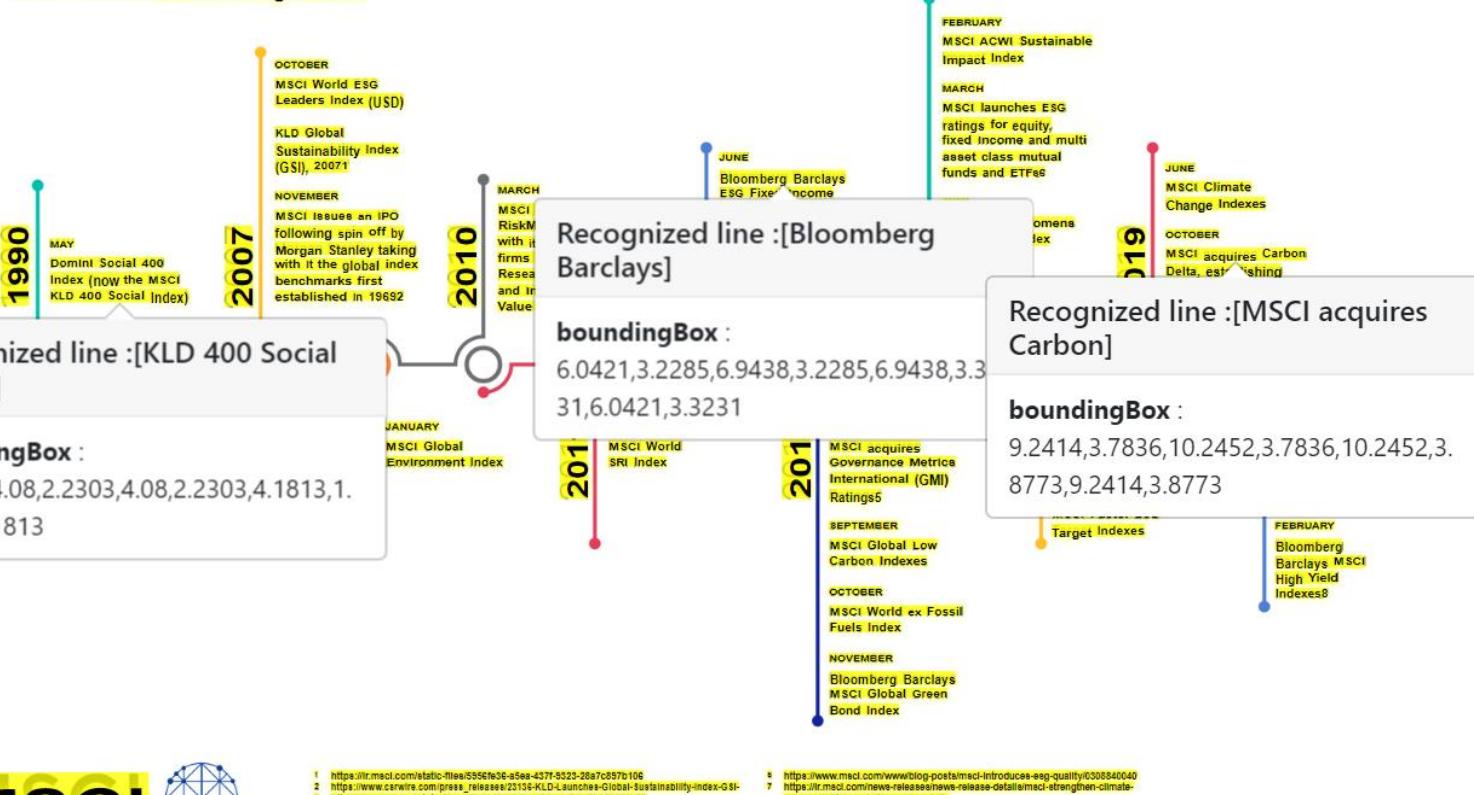


Visuals...

30 years of MSCI ESG Indexes

Take a look at the history of ESG indexes in our timeline below. We highlight key milestones in the evolution of ESG indexes since 1990, beginning with the launch of the Domini 400 Social Index (now the MSCI KLD 400 Social Index), through to the launch of the MSCI Fixed Income ESG Indexes in 2020. We also highlight significant developments such as MSCI's acquisition of Carbon Delta in 2019.

Learn more at [msci.com/esg-indexes](https://www.msci.com/esg-indexes)



Research Insights



China and the Future of Equity Allocations

What does the partial inclusion of China A shares in MSCI indexes mean for global and emerging market equity portfolios?

[Learn More](#)

Liquidity and Correlation in the Chinese Credit Market

China's stock market has drawn huge attention from international investors.

Recognized line :[China's stock market has drawn huge]

boundingBox :

321,456,527,456,527,472,321,471

The Rise of Fundamental Factors in China A Shares

Commonly held perceptions about China A shares have influenced investors to think factor strategies work in the Chinese equity market. Our research suggests this is changing.

[More](#)



Stress Testing US-China Trade Wars

Amid ongoing U.S.-China trade tension, we have updated our stress test to consider three scenarios for how the situation could unfold – and their impact on currency, bond and equity markets around the world.

[Learn More](#)

Chinese Convertibles: Equities in Fancy Dress?

Chinese corporate bonds that convert to A shares display equity-like

Recognized line :[Chinese corporate bonds that convert]

boundingBox :

321,939,530,938,530,952,321,953

China Through an ESG Lens

Chinese domestic investors and issuers are moving fast to incorporate ESG considerations in their decision making, prodded by regulatory initiatives to promote ESG practices and disclosure. At the same time, shortages of skilled talent, consumer expectations around safety, growing climate risk and increased demands for shareholder rights.

[More](#)



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Mixed Languages...



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4625734 / 4625735



	Drive on the left
	Conduise a gauche
	Links fahren
	Tenere la sinistra
	Conduzca por la a izquierda
	Links rijden



Document Understanding (Form Recognizer API)

CONTOSO LTD.		INVOICE				
Contoso Headquarters 123 456 th St New York, NY, 10001		INVOICE: INV-100 INVOICE DATE: 11/15/2019 DUUE DATE: 12/15/2019 CUSTOMER NAME: MICROSOFT CORPORATION SERVICE PERIOD: 10/14/2019 – 11/14/2019 CUSTOMER ID: CID-12345				
Microsoft Corp Other St, Redmond WA, 98052						
Microsoft Finance 123 Bill St, Redmond WA, 98052		SHIP TO: Microsoft Delivery 123 Ship St, Redmond WA, 98052				
		SERVICE ADDRESS: Microsoft Services 123 Service St, Redmond WA, 98052				
SALESPERSON P.O.		NUMBER	REQUISITIONER	SHIPPED VIA	F.O.B. POINT	TERMS
		PO-3343				
QUANTITY		DESCRIPTION			UNIT PRICE	TOTAL
1		Consulting service			1	\$100.00
					SUBTOTAL	\$100.00
					SALES TAX	\$10.00
					TOTAL	\$110.00
					PREVIOUS UNPAID BALANCE	\$500.00
					TOTAL DUE	\$610.00
THANK YOU FOR YOUR BUSINESS!						
REMIT TO: Contoso Billing 123 Remit St New York, NY, 10001						

Page # / Field name / Value	Confidence
1 AmountDue	88.20%
text: \$610.00	
valueNumber: 610	
1 BillingAddress	99.70%
123 Bill St, Redmond WA, 98052	
1 BillingAddressRecipient	99.80%
Microsoft Finance	
1 CustomerAddress	99.80%
123 Other St, Redmond WA, 98052	
1 CustomerAddressRecipient	99.70%
Microsoft Corp	
1 CustomerId	98.00%
CID-12345	
1 CustomerName	98.20%
MICROSOFT CORPORATION	
1 DueDate	99.50%
text: 12/15/2019	
valueDate: 2019-12-15	
1 InvoiceDate	99.60%
text: 11/15/2019	
valueDate: 2019-11-15	
1 Invoiceld	99.90%
INV-100	
1 InvoiceTotal	98.90%
text: \$110.00	
valueNumber: 110	
1 PreviousUnpaidBalance	98.90%
text: \$500.00	
valueNumber: 500	
1 PurchaseOrder	96.10%
PO-3333	

```
"documentResults": [
    {
        "docType": "TextDocument",
        "pageRange": "1-100",
        "fields": [
            {
                "name": "AmountDue",
                "type": "Text",
                "value": "7.81",
                "text": "7.81"
            },
            {
                "name": "AmountPaid",
                "type": "Text",
                "value": "7.91",
                "text": "7.91"
            },
            {
                "name": "AmountRefund",
                "type": "Text",
                "value": "7.81",
                "text": "7.81"
            },
            {
                "name": "AmountRemaining",
                "type": "Text",
                "value": "7.91",
                "text": "7.91"
            },
            {
                "name": "AmountTotal",
                "type": "Text",
                "value": "7.95",
                "text": "7.95"
            },
            {
                "name": "PageCount",
                "type": "Text",
                "value": "7.38",
                "text": "7.38"
            },
            {
                "name": "PageNumber",
                "type": "Text",
                "value": "7.95",
                "text": "7.95"
            },
            {
                "name": "Comments",
                "type": "Text",
                "value": "7.95",
                "text": "7.95"
            },
            {
                "name": "ElementCount",
                "type": "Text",
                "value": "7.95",
                "text": "7.95"
            }
        ],
        "BillingPeriod": [
            {
                "type": "Text",
                "value": "4.37",
                "text": "4.37"
            },
            {
                "type": "Text",
                "value": "2.01",
                "text": "2.01"
            },
            {
                "type": "Text",
                "value": "4.37",
                "text": "4.37"
            },
            {
                "type": "Text",
                "value": "2.01",
                "text": "2.01"
            },
            {
                "type": "Text",
                "value": "4.71",
                "text": "4.71"
            },
            {
                "type": "Text",
                "value": "0.59",
                "text": "0.59"
            },
            {
                "type": "Text",
                "value": "4.71",
                "text": "4.71"
            },
            {
                "type": "Text",
                "value": "#/row",
                "text": "#/row"
            }
        ],
        "BillingPeriodCount": [
            {
                "type": "Text",
                "value": "7.95",
                "text": "7.95"
            }
        ]
    }
]
```

Form Recognizer

Data extraction in any business process that intakes forms and outputs structured data



Layout



Prebuilt[s]

The image displays three distinct document forms side-by-side:

- Construction Bid Form:** A form titled "Construction Bid Form" with sections for "Owner Information" (Name: Anderson, Address: 124-568) and "Contractor Information" (Company: Contoso, Name: John Doe, Address: 123 Main Street, City: Sunnyvale, State: CA, ZIP: 94089). It includes a "Health Progress Chart" table and a "CREDIT CARD AUTHORIZAT" section.
- Credit Application:** A form titled "CREDIT APPLICATION" with sections for "APPLICANT INFORMATION" (Name: Contoso, Ltd., SSN: 123-45-6789, Date of Birth: 01/01/1980, Current Address: 102 Enterprise Way, Sunnyvale, CA, USA, 91111), "EMPLOYMENT INFORMATION" (Employer: Contoso, Ltd., Job Title: 2018, Term: 1000), and "Mortgage Interest Statement".
- Finance Proposal Form:** A form titled "Finance Proposal Form" with sections for "SUPPLIER FINANCE" (Hotel: [redacted]), "CUSTOMER DETAILS" (Company Name: [redacted], Industry: [redacted], Postcode: [redacted], Nature of Business: [redacted], Year established: [redacted], Business Premises: [redacted], Leasehold: [redacted]), and "LEASE DETAILS" (Term: [redacted], Payment Profile: [redacted], Total Sales Value: [redacted], Delivery Date: [redacted]).

Custom

An Atypical Language Understanding Problem

様式 I
FORM

税務署長様
税務署長様

租税条約に関する届出書
APPLICATION FORM FOR INCOME TAX CONVENTION

配当に対する特典及び復興特別所得税の軽減・免除
Relief from Japanese Income Tax and Special Income Tax for Reconstruction or Dividends

税務署長様
For official use only

適用：有、無

Recognized line :[Relief from Japanese Income Tax and Special Income]

boundingBox :
3.2059,1.1748,5.8717,1.1748,5.8717,1.26
89,3.2059,1.2689

appearance.style : print
appearance.styleConfidence : 1

三 税度税率 %
Applicable Tax Rate

三 免 稅 Exemption

電話番号 Telephone Number

氏名又は
Full name

個人の場合 Individual

住所又は
Domicile or residence

國 Nationality

本店又は主たる事務所の所在地 Place of head office or main office

設立又は組織された場所 Place where the Corporation was established or organized

事業が管理・支配されている場所 Place where the business is managed and controlled

電話番号 Telephone Number

下記「4」の配当について居住者として課税される國及び納稅地を記入する欄
Country where the recipient is to pay tax on Dividends mentioned

日本国内の恒久的施設 Permanent establishment in Japan

（有）Yes, （無）No If "Yes", explain:

3 配当の支払者に関する事項 Details of Payer of Dividends

(1) 名
Name

(2) 本店 Place

(3) 法人 Corporation

(4) 発行済株式のうち Number of voting shares

上記「3」の支払者から支払を受けた配当で「1」の租税条約の規定の適用を受けるものに関する事項 (注 10) ;]

Recognized line :[上記「3」の支払者から支払を受けた配当で「1」の租税条約の規定の適用を受けるものに関する事項 (注 10) ;]

boundingBox :
0.8577,8.7963,6.4117,8.7963,6.4117,8.89
66,0.8577,8.8966

appearance.style : print
appearance.styleConfidence : 1

上記「3」の支払者から支払を受けた配当で「1」の租税条約の規定の適用を受けるものに関する事項 (注 10) ;]

Details of Dividends received from the Payer to which the Convention mentioned in 1 above is applicable (Note 10)

元本の種類	銘柄又は登録名	名義人の氏名又は名前 (注 11)
出資株式基金 Share Stocks		
株式投資信託 Stock investment trust		

元本の額	うち議決権のある株式数	元本の取扱年月日
Quantity of Principal	Of which Quantity of Voting Shares	Date of Acquisition of Principal

Not all documents can have a clear read order... Can we still extract knowledge like key-value pairs?

Visual Linguistic Tasks

Visual Question Answering

Who is wearing glasses?
man woman



Is the umbrella upside down?
yes no



Where is the child sitting?
fridge arms



How many children are in the bed?
2 1



Image Captioning



Image-Text Retrieval

Query: A man riding a motorcycle is performing a trick at a track .

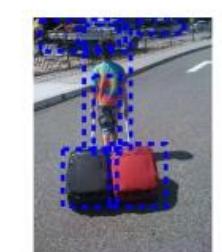


Query: Two dogs play by a tree .

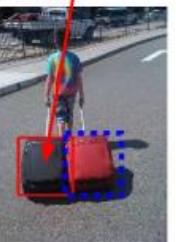


- 1:A female runner dressed in blue athletic wear is running in a competition , while spectators line the street . ✓
- 2:A lady dressed in blue running a marathon . ✓
- 3:A young woman is running a marathon in a light blue tank top and spandex shorts . ✓
- 4:A lady standing at a crosswalk . ✗
- 5:A woman who is running , with blue shorts . ✓

Referred Expression Comprehension



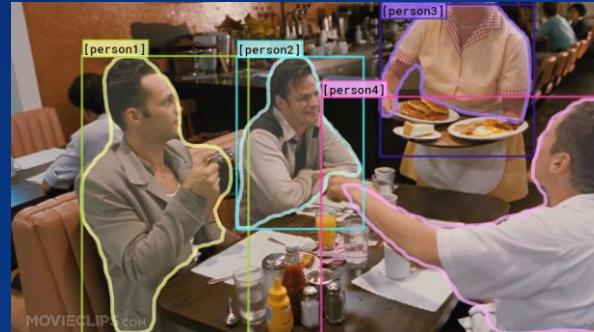
A black carry-on suitcase with wheels



The truck in the background.



Visual Commonsense Reasoning



Why is [person4] pointing at [person1]?

- a) He is telling [person3] that [person1] ordered the pancakes.
- b) He just told a joke.
- c) He is feeling accusatory towards [person1].
- d) He is giving [person1] directions.

Some Representative Works on Visual-Linguistic Joint Modeling

- VideoBERT: A Joint Model for Video and Language Representation Learning, Chen Sun, Austin Myers, Carl Vondrick, Kevin Murphy, Cordelia Schmid, ICCV 2019.
- ViLBERT: Pretraining Task-Agnostic Visiolinguistic Representations for Vision-and-Language Tasks, Jiasen Lu, Dhruv Batra, Devi Parikh, Stefan Lee, NIPS 2019.
- LXMERT: Learning Cross-Modality Encoder Representations from Transformers, Hao Tan, Mohit Bansal, EMNLP 2019.
- Unicoder-VL: A Universal Encoder for Vision and Language by Cross-modal Pre-training, Gen Li, Nan Duan, Yuejian Fang, Ming Gong, Dixin Jiang, Ming Zhou, AAAI 2020.
- VL-BERT: Pre-training of Generic Visual-Linguistic Representations, Weijie Su, Xizhou Zhu, Yue Cao, Bin Li, Lewei Lu, Furu Wei, Jifeng Dai, ICLR 2020.

Focusing More on Documents

- Yang et al.^[1] presented an end-to-end, multimodal, fully convolutional network for extracting semantic structures.
- Liu et al.^[2] introduced a Graph Convolutional Networks (GCN) based model to combine textual and visual information.
- Davis et al. ^[3] proposed to use relationship classifier and neighbor prediction networks to identify key-value pairs.
- Sarkhel et al. ^[4] proposed a multi-scale classification method to classify the visually rich document.

[1] Yang, Xiaowei et al. "Learning to Extract Semantic Structure from Documents Using Multimodal Fully Convolutional Neural Networks." CVPR (2017).

[2] Liu, Xiaojing et al. "Graph Convolution for Multimodal Information Extraction from Visually Rich Documents." NAACL-HLT (2019).

[3] Davis, Brian et al. "Deep Visual Template-Free Form Parsing." ICDAR (2019).

[4] Sarkhel, Ritesh and Arnab Nandi. "Deterministic Routing between Layout Abstractions for Multi-Scale Classification of Visually Rich Documents." IJCAI (2019).

Report

Form

Receipt

Invoice

UBS

Global Research

31 January 2018

First Read

Microsoft Corp.

Azure Acceleration Impresses in Solid Q2

Good Q2 With More to Come

Microsoft posted a clean beat with revenue, margins, and EPS all topping Street expectations and X18/19 estimates moving higher. With shares +11% YTD, some of the good news is likely already priced in, but given the backdrop of accelerating Azure growth, we believe Microsoft is well positioned to benefit from IT spending. If we are right on the back of tax reform, we see more beats ahead and continue to recommend the stock while our price target from \$105 to \$110 on the back of our FY18 and FY19 estimates moving higher.

Azure Acceleration

Azure acceleration of 98% was the strongest in Q2, while Azure margins continued to show strong improvement year-over-year. Overall Cloud GM did modestly up 50% from 57% in Q1 due to seasonality impacts linked to the timing of overage payments for some Azure contracts as well as Azure comprising a bigger piece of revenue. We expect Azure to continue to accelerate as we raised our FY18 estimate by \$1.82 of new Azure rev. YTD for each of \$4.00 C/COGS, up from +\$1.55 in the prior 2 Qs and highlighting expanding margins in the Azure business.

Revenue Beat and Future Benefits Drive Estimates Higher

Gross and operating margin upside in Q2 drives margin expectations higher for the year. We expect revenue to grow 10% in 2018, a slight increase in CY18 for FY18. Our FY18 rev. est. moves from \$16.6B to \$17.0B while FY19 goes from \$11.6B to \$11.7B. Microsoft now expects -10.6% tax rate for X18/19 and just under 10% for X20/21. We also believe the recent 10% cut to X18/19 EPS estimates moved to \$3.62 (\$3.35 prior) while FY19 moves to \$4.02 (\$3.37 prior).

Valuation: PT moves 5% higher to \$110 (\$105 prior) on positive revision

We value Microsoft's Cloud businesses using a SaaS multiple, which moves from 6.2x EV/CFY18 to 6.8x due to better growth and better FCF margins in the Cloud business, as well as broader adoption across the SaaS group; while better cash flow also increases our valuation for the legacy on-prem businesses which we value assuming 3% annual decline in perpetuity with a 5% discount rate.

Equities

Americas Software

12-month rating Buy

12m price target US\$110.00

Price: US\$105.00

Price/Sales US\$55.01

RC: M\$FT D B&G: M\$FT US

Trading data and key metrics

US\$95.01-03-13

Market cap. US\$374bn

Shares outstanding 7.72Bn

Free float 90%

Avg. daily volume ('000) 23,992

EPS (diluted) US\$2.05

EPS (fwd 12M) US\$19.05

P/E (FY18) 7.0x

Net debt/EBITDA (FY18) NM

EPS (FY18) diluted (US\$)

From To % ch Cons.

Q1 0.84 0.84 0.00 11.36

Q2 0.84 0.84 0.00 11.36

Q3 0.75 0.83 0.08 0.78

Q4 0.89 0.99 0.11 0.91

FY18E 3.62 3.62 0.00 5.42

FY19E 3.78 4.02 0.06 3.80

FY20E 4.41 4.67 0.26 4.41

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Highlights (US\$mn)

06/15 06/16 06/17 06/18E 06/19E 06/20E 06/21E

Revenue 306.47 329.47 346.27 350.47 347.47 347.47 347.47

EBITDA 28.172 27.168 29.331 32.724 36.812 45.469 52.903

Net income (loss) (US\$B) 2.62 2.66 2.79 3.02 3.01 3.64 3.63

DPS (US\$) 2.11 2.44 1.53 2.09 1.77 1.80 1.80

Free cash flow (US\$B) 6.12 5.29 4.04 4.07 10.66 13.80 13.80

Dividends paid (US\$B) 5.03 5.29 4.07 4.07 10.66 13.80 13.80

Profitability/valuation

06/15 06/16 06/17 06/18E 06/19E 06/20E 06/21E

EBIT margin % 30.1 29.8 30.4 30.5 33.1 35.1 37.1

ROE % 12.9 13.0 13.2 13.0 13.4 13.5 14.3

EV/EBITDA (cons.) x 8.7 9.8 11.4 15.5 10.5 8.6 7.0

EPS (diluted) US\$ 1.12 1.22 1.34 1.44 1.77 1.80 1.80

Equity/FCF (US\$) 6.2 6.1 6.4 5.9 4.3 5.1 6.1

Net dividend yield % 2.7 2.5 2.4 2.3 2.1 2.0 2.0

Source: UBS Research, Thomson Financial, SEC 10-K reports. All data is based on post-revenue restatement and other adjustments for abnormal and economic items, net of analysis.

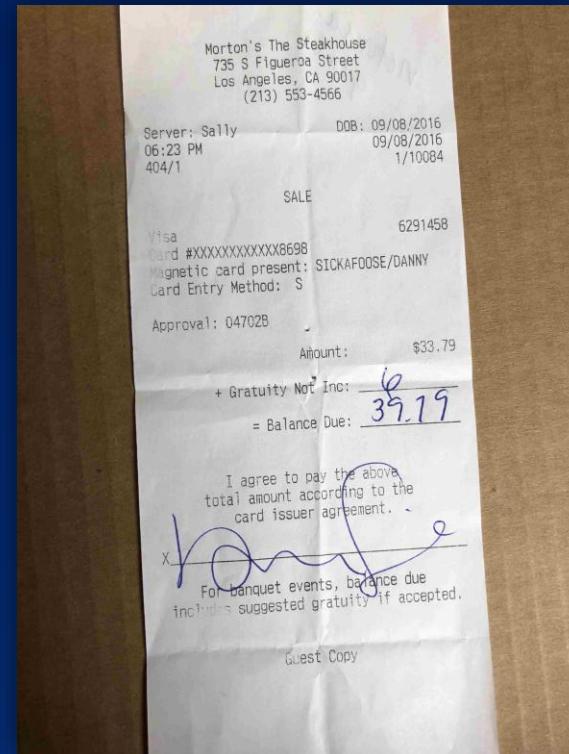
Note: EPS is based on a forward-looking earnings per share figure. P/E is based on a share price of US\$95.01 on 31 Jan 2018 (US\$4.07

www.ubs.investmentresearch

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16

ACUTE TOXICITY IN MICE					
COMPOUND <u>3-Hydroxy-3-methylbutanoic acid (Tur 13)</u>					
SOURCE <u>Lorillard = Organic Chemistry</u>	LORILLARD NO.	OR39-23	TEST NO.	<u>44</u>	DATE RECEIVED <u>Unk.</u>
DATE RECEIVED <u>Unk.</u>	TESTED <u>12/28/78</u>	REPORTED <u>10/6/80</u>	NOTEBOOK PAGE	<u>bio14-23</u>	INVESTIGATOR(S) <u>H. S. Tong & M. S. Forte'</u>
SIGNATURE(S) <u>H. S. Tong</u> <u>M. S. Forte (by A. Poole)</u>					
STRAIN OF MICE <u>Swiss-Webster</u>	MALE <input checked="" type="checkbox"/>	FEMALE <input type="checkbox"/>	DATE RECEIVED	Unk.	
AVERAGE WEIGHT RANGE (GM)	SOURCE <u>Camm Research</u>				
ROUTE OF COMPOUND ADMINISTRATION <input checked="" type="checkbox"/> P.O. <input type="checkbox"/> I.P. <input type="checkbox"/> I.V. <input type="checkbox"/> INHALATION					
COMPOUND VEHICLE <input checked="" type="checkbox"/> 5% METHYL CELULOSE <input type="checkbox"/> COPROPSYLIC OIL <input type="checkbox"/> SALINE <input type="checkbox"/> OTHER					
GROUP NO.	% SOLUTION	DOSAGE (mg/kg BODY WEIGHT)	RESULTS (NO. DEATHS/TESTED)		
1	5	1800	1/6		
2	10	2160	0/6		
3	10	2592	0/6		
4	10	3732	3/6		
5	10	4479	6/6		
REFERENCE FOR CALCULATION <u>Litchfield, J. T. and Wilcoxin, F., J. of Pharmacol. and Exper. Ther., 90:99, 1948.</u>					
LD ₅₀ (95% CONFIDENCE LIMITS) <u>3.5 (3.1 to 3.9) g/kg</u>					
CONCLUSION <u>This compound appears to act as a CNS depressant with symptoms of respiratory depression, constriction of blood vessels, and inactivity. Survivors recovered in 48 hours. The recommended safe dose for a single trial by inhalation in man is 0.3 mg.</u>					
Copies to the Following: Dr. H. J. Minnemeyer MS. L. B. Gray					
LORILLARD RESEARCH CENTER					
FORM 7 (5-80)					



Page 1 of 1

Invoice

1 877 FileLine | InformationProtected.com

New Belgian Brewery Company
A/c: Accounts Payable Manager
500 Linden St
Ft Collins, CO 80524

Service Billing Period: 1/31/2017
Date: 1/31/2017
Invoice #: 1861619
Customer #: GDP96286

Total Amount Due: \$546.69
By 3/2/2017
Total Enclosed:
130GDP05206

Remit To: PO Box 398303 San Francisco, CA 94139-8303

When making payment, please reference invoice number 1861619

NOTE: MAIN

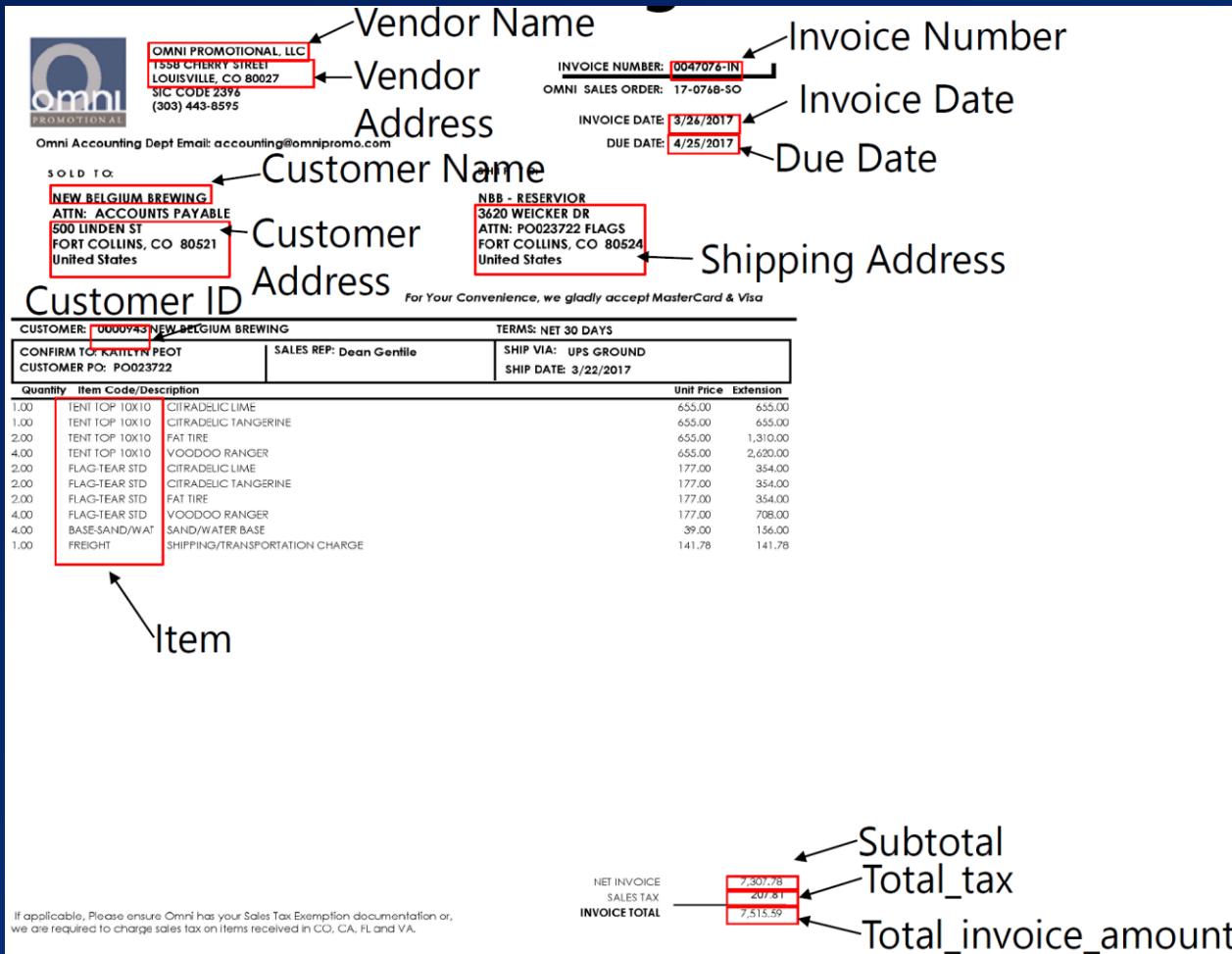
QTY ITEMS	SERVICE DESCRIPTION	QUANTITY	RATE	TAX	FEES	
Storage						
Storage Period: 02/01/2017 - 02/28/2017						
4	Local Bankers Box	10.00	0.5040	N	5.04	
468	Letter Bankers Box	936.00	0.5040	N	477.76	
85	Letter Legal Box	85.00	0.5400	N	45.90	
	TOTAL FOR Storage	1,031.00			522.69	
	TAX				.69	
Service						
	File Tracking	3.00	0.0000	N	0.00	
	Medium console - Initial Delivery	3.00	0.0000	N	0.00	
	Medium Console - Scheduled Rotation / Plant	3.00	0.0000	N	0.00	
	Container Refile	4.00	6.0000	N	24.00	
	FILEBLUETO: Records + AccessMETRICS	1.00	0.0000	N	0.00	
	TOTAL FOR Service				24.00	
	TAX				0.00	
Transportation						
	Shred Rotation Transportation - Scheduled trip	2.00	0.0000	N	0.00	
	TOTAL FOR Transportation				0.00	
	TAX				0.00	
				SUB-TOTAL	646.69	
				TAX	0.00	
					INVOICE TOTAL	646.69

PLEASE NOTE: To the extent you do not have a currently effective written contract for services with an Access or Retrieves company, by paying this invoice, you agree that the terms and conditions found on <http://informationprotected.com/access-service-terms-and-conditions> (December 1, 2015 version) will apply to and govern the storage, document destruction, imaging and other services provided to you by such company and, therefore, **WILL AFFECT YOUR LEGAL RIGHTS AND OBLIGATIONS, AND LIMITS OUR LIABILITY TO YOU**. However, if you have a currently effective written contract for services with an Access or Retrieves company, the terms and conditions of your written contract will supersede any terms in such contract. Further, if you are a "Covered Entity" or "Business Associate" as defined in 45 CFR part 160 and do not have a currently effective written Business Associate Agreement (BAA) or Business Associate Subcontractor Agreement (BASA) with an Access or Retrieves company, by paying this invoice, you agree that the terms and conditions found on www.informationprotected.com/baa constitute a legally effective BAA or BASA, as applicable, between you and such Access or Retrieves company. As determined appropriate by Access, purchases that do not reference a specific invoice will be applied to the oldest outstanding invoice. Terms or conditions on purchase orders or similar documents submitted to an Access or Retrieves are not binding.

Document Understanding in Real World

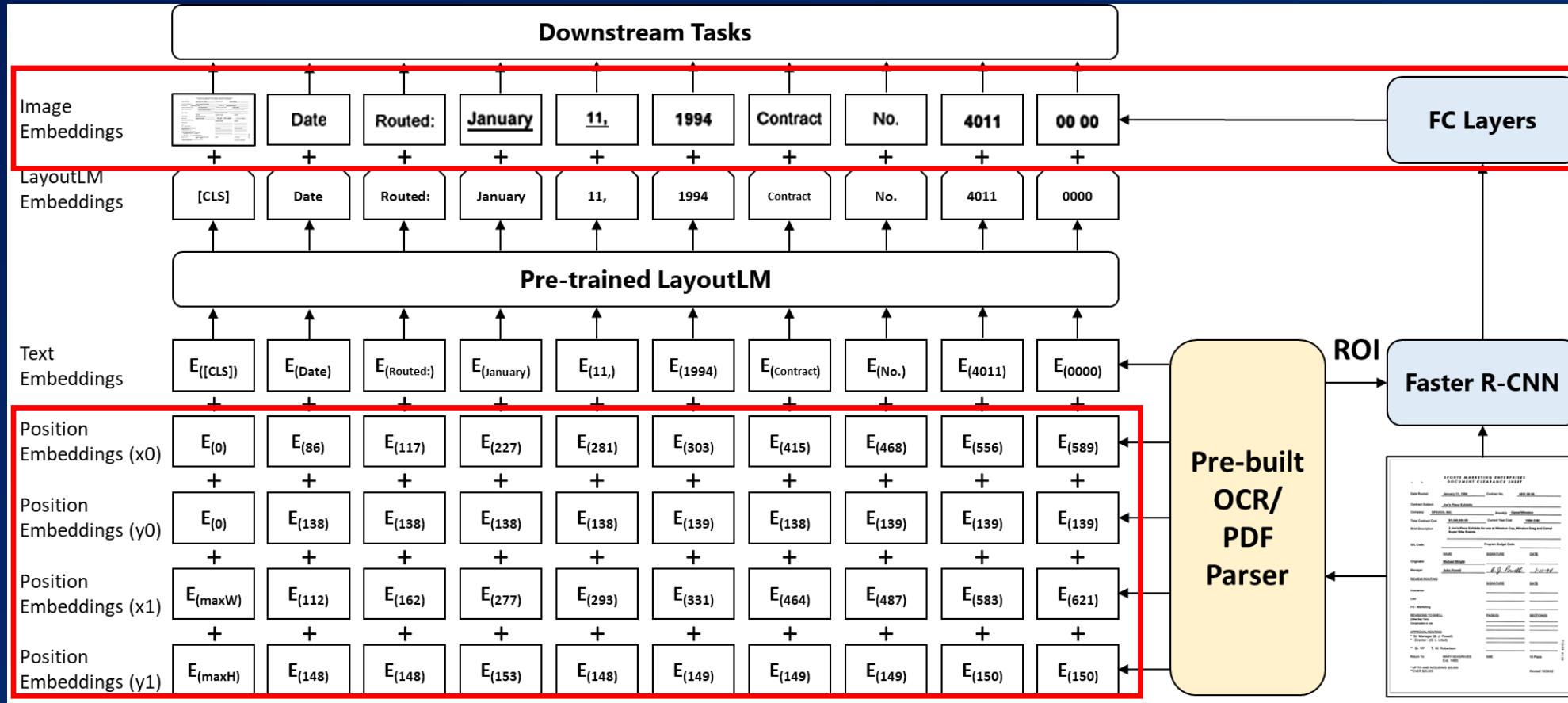
LayoutLM: Pre-training for **Text** with rich **Layout** and **Style** information [1]

Example: Invoice Understanding



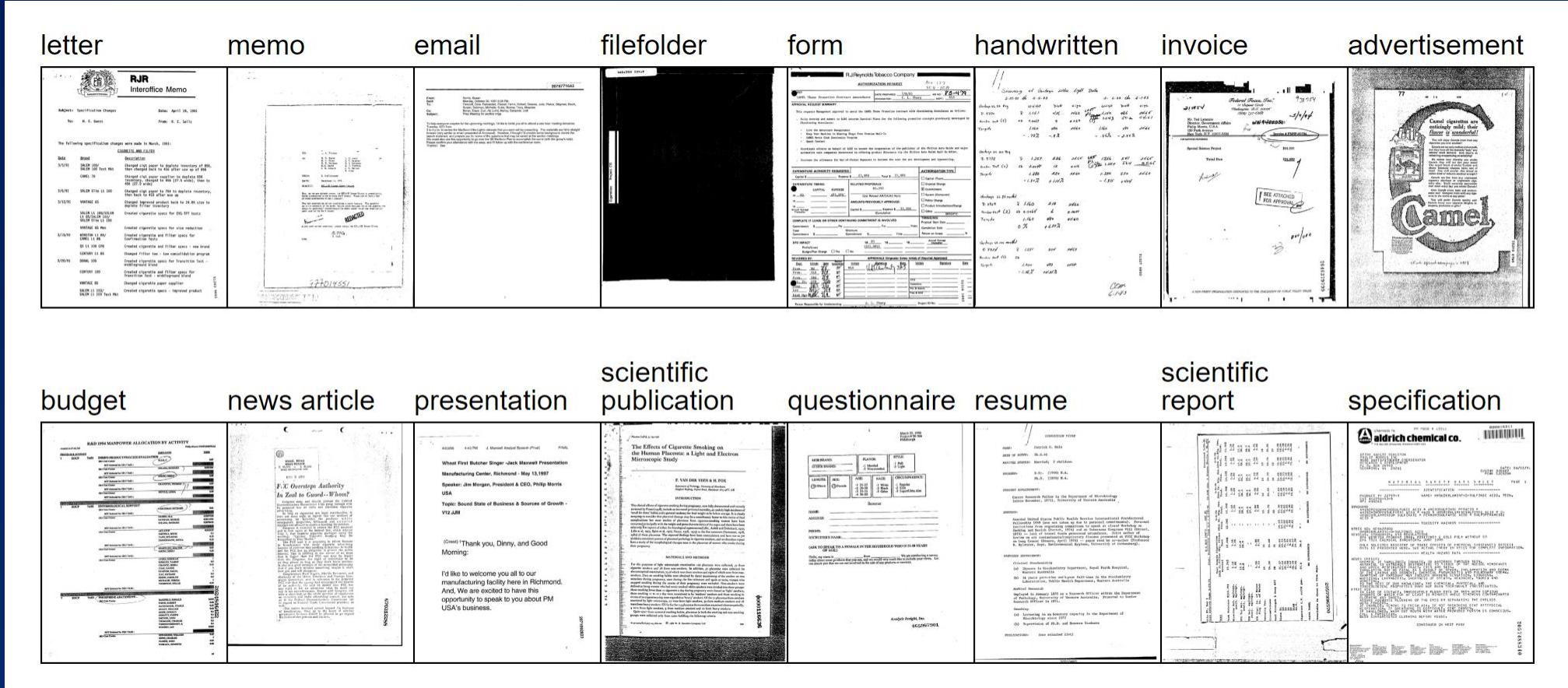
- Date
- ID
- Number
- Address
- Name
- Item
- ...

LayoutLM Architecture



* Text embeddings initialized by BERT/UniLM

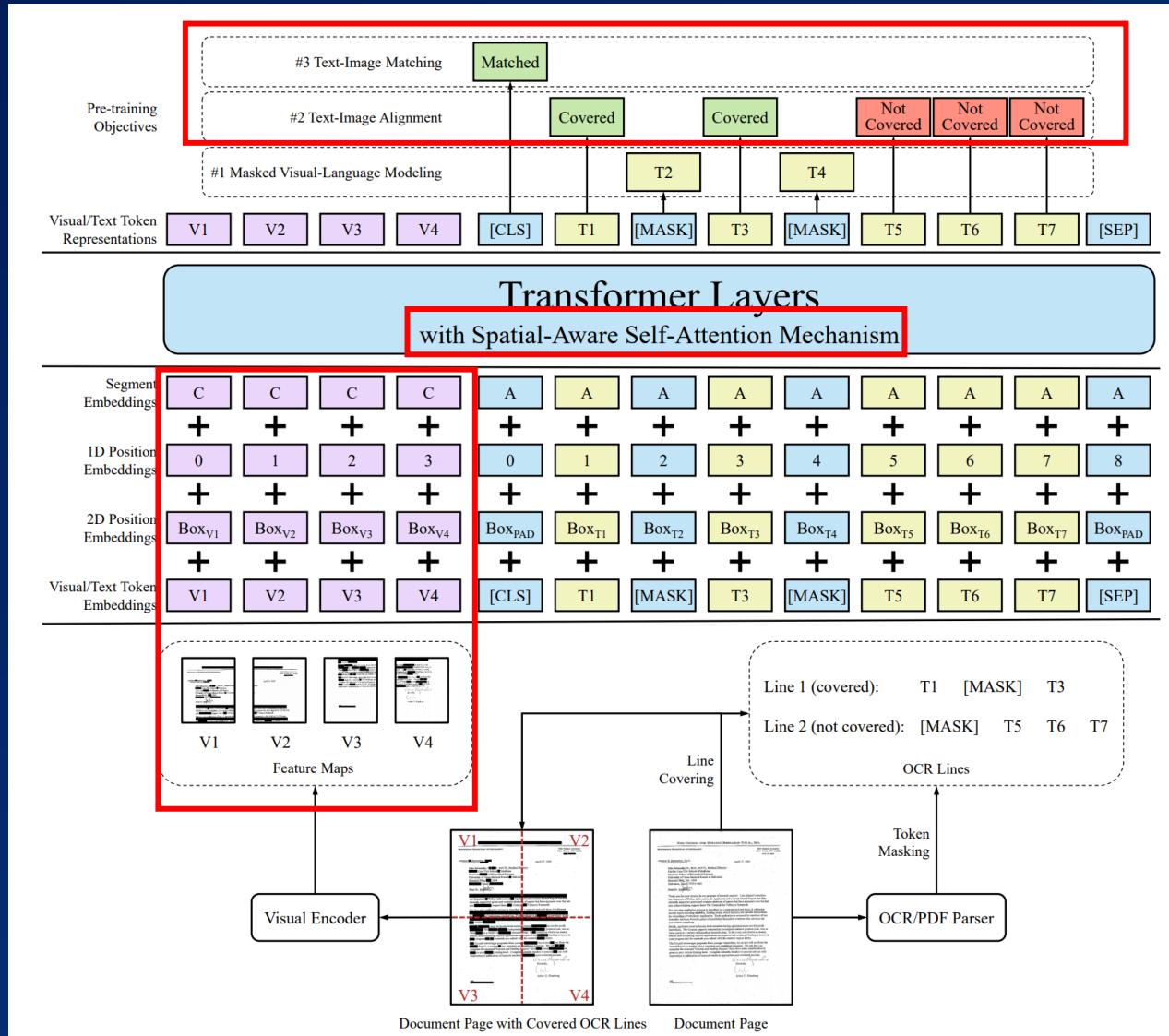
Pre-training Data



11 million scanned document images from IIT-CDIP Test Collection 1.0
<https://ir.nist.gov/cdip/>

LayoutLMv2

LayoutLMv2: Multi-modal Pre-training for Visually-Rich Document Understanding, ACL 2021



- New pre-training tasks
- New self-attention mechanism
- Image features now go through transform layers

Semantic Entity Recognition

Model	FUNSD	CORD	SROIE	Kleister-NDA
BERT _{BASE}	0.6026	0.8968	0.9099	0.7790
UniLMv2 _{BASE}	0.6648	0.9092	0.9459	0.7950
BERT _{LARGE}	0.6563	0.9025	0.9200	0.7910
UniLMv2 _{LARGE}	0.7072	0.9205	0.9488	0.8180
LayoutLM _{BASE}	0.7866	0.9472	0.9438	0.8270
LayoutLM _{LARGE}	0.7895	0.9493	0.9524	0.8340
LayoutLMv2 _{BASE}	0.8276	0.9495	0.9625	0.8330
LayoutLMv2 _{LARGE}	0.8420	0.9601	0.9781	0.8520
BROS (Hong et al., 2021)	0.8121	0.9536	0.9548	–
SPADE (Hwang et al., 2020)	–	0.9150	–	–
PICK (Yu et al., 2020)	–	–	0.9612	–
TRIE (Zhang et al., 2020)	–	–	0.9618	–
Top-1 on SROIE Leaderboard (until 2020-12-24)	–	–	0.9767	–
RoBERTa _{BASE} in (Graliński et al., 2020)	–	–	–	0.7930

Form Understanding (**FUNSD**)

<https://guillaumejaume.github.io/FUNSD/>

Receipt Understanding (**SROIE, CORD**)

<https://rrc.cvc.uab.es/?ch=13>

<https://github.com/clovaai/cord>

Document Information Extraction (**Kleister-NDA**)

<https://github.com/applicaai/kleister-nda>

Document Image Classification

Model	Accuracy	#Parameters
BERT _{BASE}	89.81%	110M
UniLMv2 _{BASE}	90.06%	125M
BERT _{LARGE}	89.92%	340M
UniLMv2 _{LARGE}	90.20%	355M
LayoutLM _{BASE} (w/ image)	94.42%	160M
LayoutLM _{LARGE} (w/ image)	94.43%	390M
LayoutLMv2 _{BASE}	95.25%	200M
LayoutLMv2 _{LARGE}	95.64%	426M
VGG-16 (Afzal et al., 2017)	90.97%	-
Single model (Das et al., 2018)	91.11%	-
Ensemble (Das et al., 2018)	92.21%	-
InceptionResNetV2 ⁶ (Szegedy et al., 2016)	92.63%	-
LadderNet (Sarkhel & Nandi, 2019)	92.77%	-
Single model (Dauphinee et al., 2019)	93.03%	-
Ensemble (Dauphinee et al., 2019)	93.07%	-

Document Image Classification (**RVL-CDIP**)

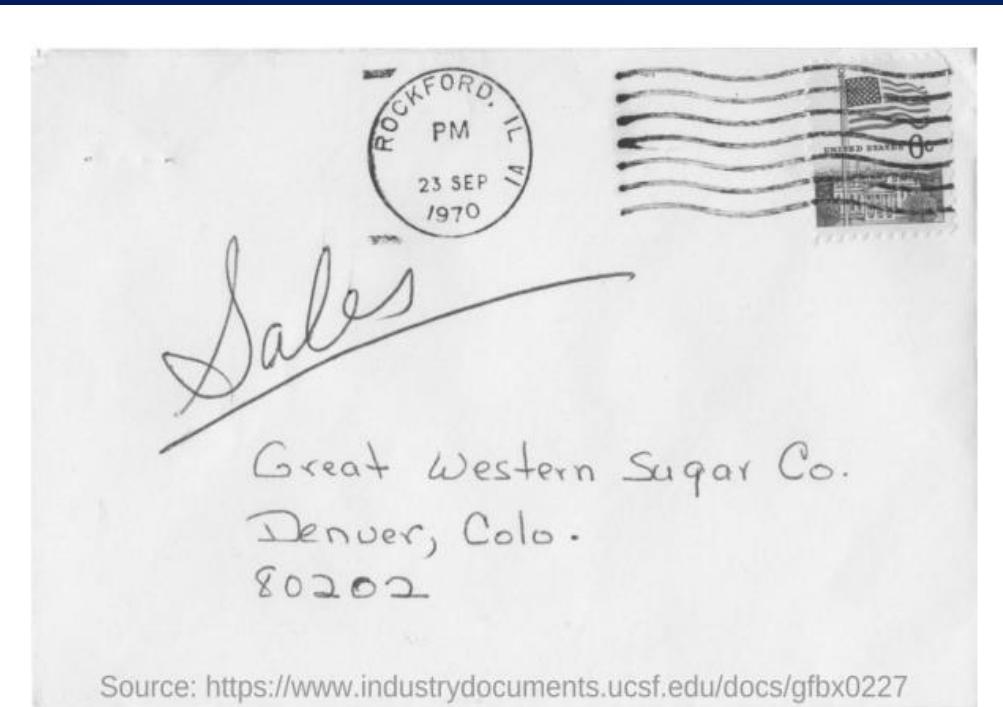
<https://www.cs.cmu.edu/~aharley/rvl-cdip/>

Document VQA

Model	Fine-tuning set	ANLS	#Parameters
BERT _{BASE}	train	0.6354	110M
UniLMv2 _{BASE}	train	0.7134	125M
BERT _{LARGE}	train	0.6768	340M
UniLMv2 _{LARGE}	train	0.7709	355M
LayoutLM _{BASE}	train	0.6979	113M
LayoutLM _{LARGE}	train	0.7259	343M
LayoutLMv2 _{BASE}	train	0.7808	200M
LayoutLMv2 _{LARGE}	train	0.8348	426M
LayoutLMv2 _{LARGE}	train + dev	0.8529	426M
LayoutLMv2 _{LARGE} + QG	train + dev	0.8672	426M
Top-1 on DocVQA Leaderboard (30 models ensemble) ⁷	-	0.8506	-

Document Visual Question Answering (*DocVQA*)
<https://rrc.cvc.uab.es/?ch=17>

DocVQA Leaderboard



Q: Mention the ZIP code written?

A: 80202

Q: What date is seen on the seal at the top of the letter?

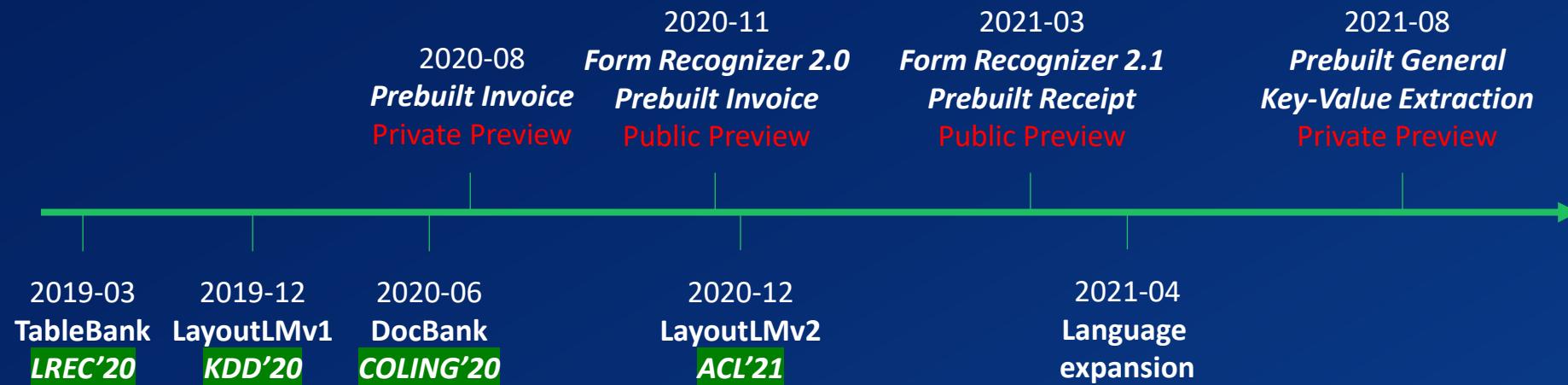
A: 23 sep 1970

Q: Which company address is mentioned on the letter?

A: Great western sugar Co.

Ranking Table ⓘ											
Date	Method	Score	Figure/Diagram	Form	Table/List	Layout	Free_text	Image/Photo	Handwritten	Yes/No	Others
2020-06-13	Human Performance	0.9811	0.9756	0.9825	0.9780	0.9845	0.9839	0.9740	0.9717	0.9974	0.9828
2020-12-22	LayoutLM 2.0 (single model)	0.8672	0.6574	0.8953	0.8769	0.8791	0.8707	0.7287	0.6729	0.5517	0.8103
2020-08-16	Alibaba DAMO NLP	0.8506	0.6650	0.8809	0.8552	0.8733	0.8397	0.6758	0.7691	0.5492	0.7526
2020-05-16	PingAn-OneConnect-Gammalab-DQA	0.8484	0.6059	0.9021	0.8463	0.8730	0.8337	0.5812	0.7692	0.5172	0.7289
2020-05-14	Structural LM-v2	0.7674	0.4931	0.8381	0.7621	0.7924	0.7596	0.4756	0.6282	0.5517	0.6549
2020-05-15	QA_Base_MRC_2	0.7415	0.4854	0.8015	0.6738	0.7943	0.8136	0.5740	0.5831	0.5287	0.7161
2020-05-15	QA_Base_MRC_1	0.7407	0.4890	0.7984	0.6675	0.7936	0.8131	0.5854	0.6099	0.4943	0.7384
2020-05-15	QA_Base_MRC_4	0.7348	0.4735	0.8040	0.6647	0.7838	0.8043	0.5618	0.5810	0.4598	0.7332
2020-05-15	QA_Base_MRC_3	0.7322	0.4852	0.7958	0.6562	0.7842	0.8044	0.5679	0.5730	0.4511	0.7171
2020-05-15	QA_Base_MRC_5	0.7274	0.4858	0.7877	0.6550	0.7754	0.8047	0.5405	0.5619	0.4598	0.7084
2020-05-16	HyperDQA_V4	0.6893	0.3874	0.7792	0.6309	0.7478	0.7187	0.4867	0.5630	0.4138	0.5685
2020-05-16	HyperDQA_V3	0.6769	0.3876	0.7774	0.6167	0.7332	0.6961	0.4296	0.5373	0.4138	0.5650
2020-05-16	HyperDQA_V2	0.6734	0.3818	0.7666	0.6110	0.7332	0.6867	0.4834	0.5560	0.3793	0.5902
2020-05-09	HyperDQA_V1	0.6717	0.4013	0.7693	0.6197	0.7167	0.6922	0.3598	0.5596	0.4138	0.5504
2020-05-09	bert fulldata fintuned	0.5900	0.4169	0.6870	0.4269	0.6710	0.7315	0.5124	0.4900	0.4483	0.5907
2020-05-01	bert finetuned	0.5872	0.2986	0.7011	0.4849	0.6359	0.6933	0.4622	0.4751	0.4483	0.4895
2020-04-30	HyperDQA_V0	0.5715	0.3131	0.6780	0.4732	0.6630	0.5716	0.3623	0.4351	0.3793	0.4941
2020-04-27	bert	0.4557	0.2233	0.5259	0.2633	0.5113	0.7775	0.4859	0.3565	0.0345	0.5778
2020-05-16	UGLIFT v0.1 (Clova OCR)	0.4417	0.1766	0.5600	0.3178	0.5340	0.4520	0.2253	0.3573	0.4483	0.3356
2020-05-14	Plain BERT QA	0.3524	0.1687	0.4489	0.2029	0.4321	0.4812	0.3517	0.3096	0.0345	0.3747
2020-05-16	Clova OCR V0	0.3489	0.0977	0.4855	0.2670	0.3811	0.3958	0.2489	0.2875	0.0345	0.3062
2020-05-01	HDNet	0.3401	0.2040	0.4688	0.2181	0.4710	0.1916	0.2488	0.2736	0.1379	0.2458
2020-05-16	CLOVA OCR	0.3296	0.1246	0.4612	0.2455	0.3622	0.3746	0.1692	0.2736	0.0690	0.3205
2020-04-29	docVQAQV_V0.1	0.3016	0.2010	0.3898	0.3810	0.2933	0.0664	0.1842	0.2736	0.1586	0.1695
2020-04-26	docVQAQV_V0	0.2342	0.1646	0.3133	0.2623	0.2483	0.0549	0.2277	0.1856	0.1034	0.1635
2020-06-16	Test Submission	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

LayoutLM for Azure Form Recognizer



[LayoutLM: Pre-training of Text and Layout for Document Image Understanding](#), KDD'20
[LayoutLMv2: Multi-modal Pre-training for Visually-rich Document Understanding](#), ACL'21

[TableBank: A Benchmark Dataset for Table Detection and Recognition](#), LREC'20
[DocBank: A Benchmark Dataset for Document Layout Analysis](#), COLING'20

Invoice Demo

Invoice Demo

Concluding Remarks

“Universal OCR” is within our reach

- Representative training data
- Scalable computing platform and training tools
- Universal text detection and mixed language/style text recognition

Document understanding – a vision/language cross-field problem

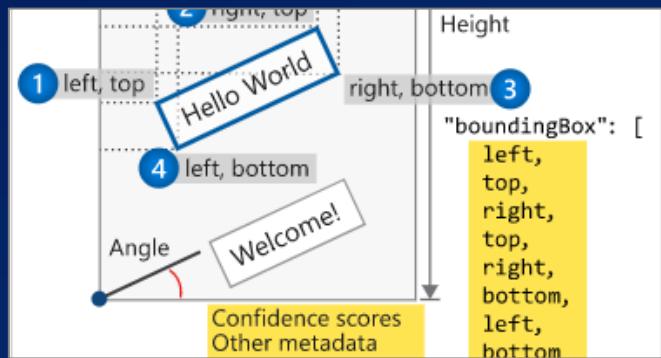
- Joint visual/language pre-training is a powerful idea
- Broadly applicable to many document understanding tasks

More researches on following topics for robotic process automation (RPA)

- Page object (especially table) detection
- Table structure recognition
- Customization

Thank you!

OCR



Form Recognizer



Contact us



<https://docs.microsoft.com/en-us/azure/cognitive-services/computer-vision/overview-ocr>

<https://docs.microsoft.com/en-us/azure/cognitive-services/form-recognizer/overview>

formrecog_contact@microsoft.com