Document Understanding in the Age of Al

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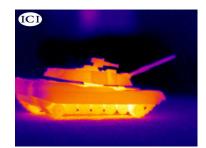
About Me

Seasoned computer vision scientist

Worked across applications in

- Document understanding
- Autonomous Driving
- In game advertising
- Defence Imaging

Multiple publications in conferences









Overview

- 1. Need for Document Understanding
- 2. Stages of Document Processing
- 3. Text Extraction In detail
- 4. Doc classification In detail
- 5. Information Extraction In detail
- 6. Conclusion

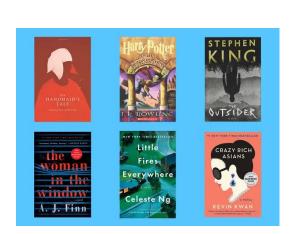
Why do we need Document Understanding

Documents are part of our everyday way of interacting and transacting with the world

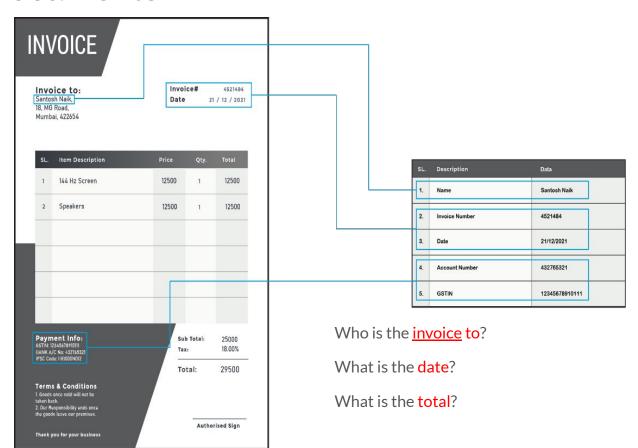
- Many types of docs Forms, texts, handwritten, certificates, legal documents
- Multiple formats images, pdfs, raw text, books
- Varied content tables, images, stylized text
- Challenges of lighting, shape, size and orientation



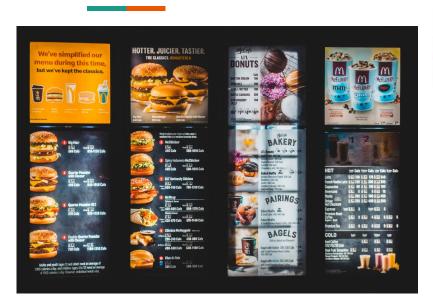
Information in Documents



What are the titles of the books?



Information in Documents



Which restaurant's menu?

What is the price of a burger? ice cream?



What is the content of the email?

What is the transaction amount?

Is it fraud/alert? Should the account be blocked?

If we can extract information, we can search and automate processes

Journey of Document Digitization

Document is input to the system

Operator <u>views</u> and <u>enters</u> fields manually

Another agent <u>verifies</u> and approves

Digitized information stored in database for later use

- 1. Time consuming
- 2. Error prone if a business decision relies on it, can lead to mishaps!
- 3. High amount of variability
 - a. Varied formats pdfs, jpegs, pngs etc
 - b. Varied layouts single column, multi column, tabular, forms
 - c. Multiple pages

Applications

If we can *automate* information extraction then we can automate business processes.

- 1. Banking, Insurance, credit card
 Customer verification, Loan document processing, email
 classification
- 2. Ecommerce and logistics
 Delivery verification, shipment processing, payment processing invoice processing





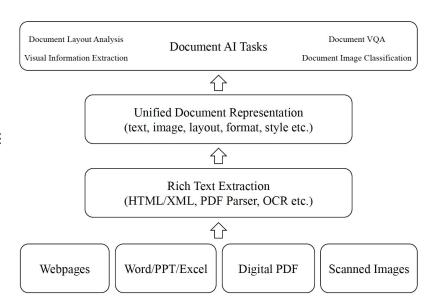
Document Processing Stages

Document understanding

Visual understanding / Text understanding / High level embeddings

Text Extraction

Input doc



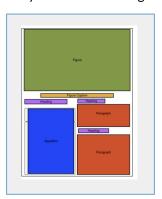
Document Understanding Tasks

Image Classification

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"type": "form",

Layout Understanding



Layout segmentation Table Detection Image Detection

Form Extraction



"company": "Brown & Williamson", "date": "19/01/1982", "product": "viceroy"

Receipt Extraction



"company": "Uroko Japanese Cusine SDN BHD", "date": "20/03/2018", "total": "53.00"

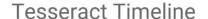
Information Extraction

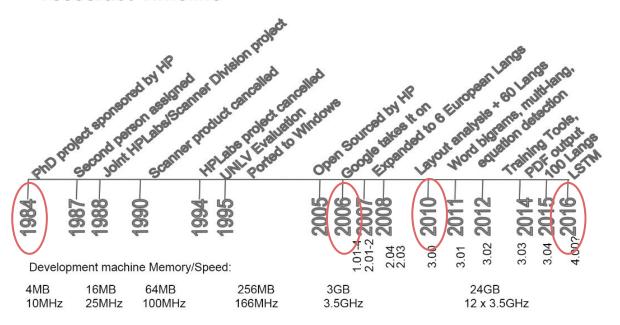
Form Understanding



Entity detection Entity Linking Visual Question Answering

From Images to Text - Optical Character Recognition





OCR - Process

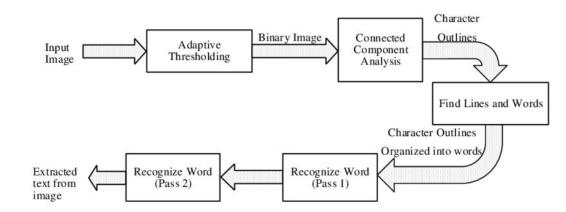
Tesseract 4.0

- 100+ languages supported
- Full layout analysis
- Table detection
- Equation detection
- Better (Deeper) language models
- Improved segmentation search
- Word bigrams
- Training tools for custom datasets

apt install tesseract-ocr

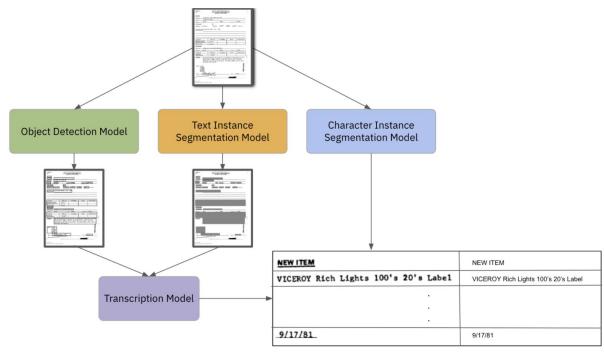






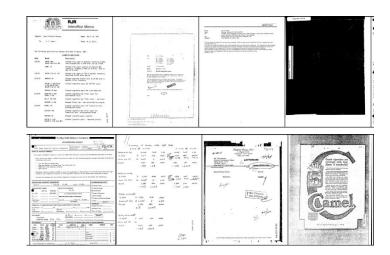
Optical Character Recognition - Modern architectures

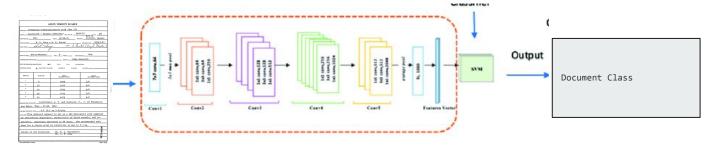
- 1. Detection Based
 - a. FAST
 - b. Faster RCNN/SSD
- Text Instance Segmentation Model
 - a. Borrowed from segmentation FCN
- Character Instance Segmentation Model



Document Image Classification

- 1. Dataset RVLCPID
 - a. 400k images
 - b. 16 categories letter, email, form, handwritten, invoice, advertisement etc.
- 2. Classification network Resnet 50
- 3. Accuracy 90%

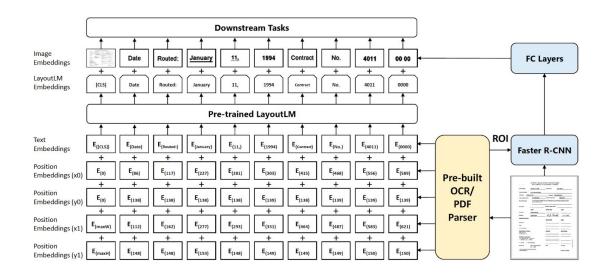




Vision + Language Models

Can we leverage vision and text to improve accuracy?

- Vision based image features with language models -LayoutLM
- Leverages the design of BERT models
- 3. Document classification Accuracy 94.5%



LayoutLM

- 1. First time that text and layout are jointly learned in a single network for document level pre-training
- 2. Two types of input embeddings in BERT Model:
 - a. 2D position embedding that denotes the relative position of a token within a document
 - b. image embedding for scanned token text within a document
- Architecture
 - Multi-task learning objective Masked Visual-Language Model (MVLM)
 loss and
 a Multi-label Document Classification
 (MDC) loss

Transformers ++: Word + position embedding

Tasks

- form understanding (from 70.72 to 79.27),
- receipt understanding (from 94.02 to 95.24) and
- document image classification (from 93.07 to 94.42).

Where to get started?

Information extraction - track finances from purchase receipts

Tesseract + LayoutLM

Result - Key value pairs of the extracted information

SROIE dataset

Information extraction from receipts

OCR text with bounding boxes

Four fields for extraction - company, date, address, total



Extracted Information

```
{
    "company": "STARBUCKS STORE
#10208",
    "address": "11302 EUCLID AVENUE,
CLEVELAND, OH (216) 229-0749",
    "date": "14/03/2015",
    "total": "4.95"
}
```

Open Research Areas in Document Understanding

Self supervised learning from large scale data

Few shot learning from scarce data

Improving image capture and preprocessing

Dealing with noise in data

Fin.

Questions?