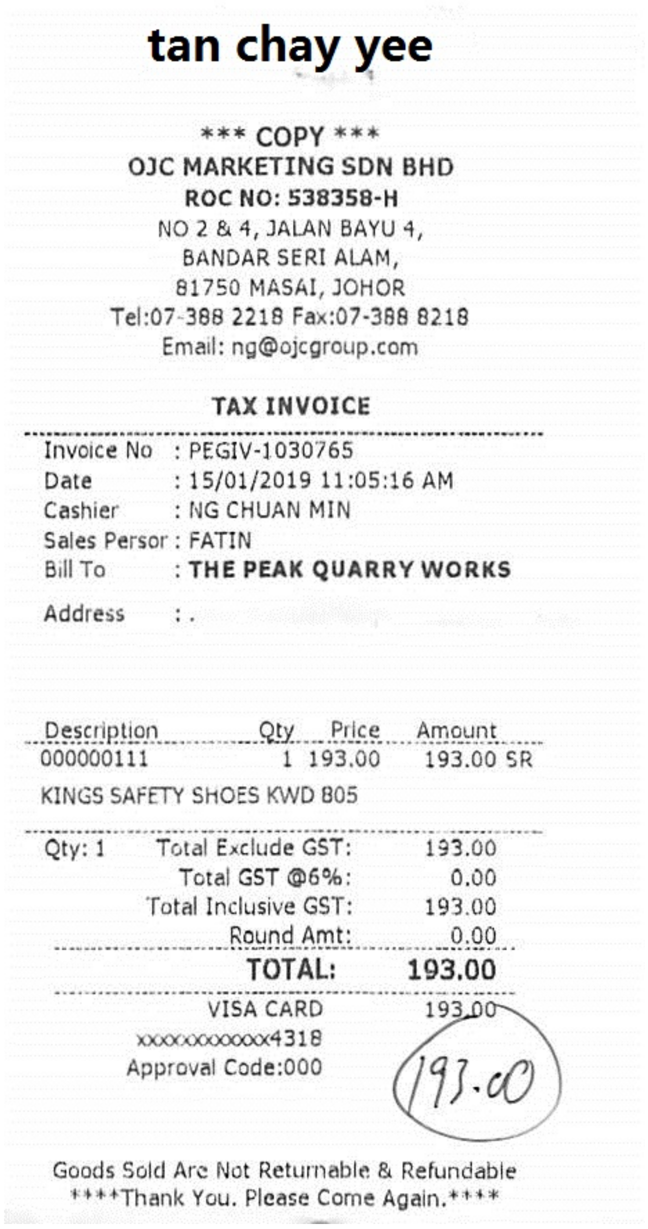
Document image understanding and information extraction tasks



tan chay yee

*** COPY ***
OJC MARKETING SDN BHD
ROC NO: 538358-H
NO 2 & 4, JALAN BAYU 4,
BANDAR SERI ALAM,
81750 MASAI, JOHOR
Tel:07-388 2218 Fax:07-388 8218
Email: ng@ojcgroup.com

TAX INVOICE

Invoice No	: PEGIV-1030765
Date	: 15/01/2019 11:05:16 AM
Cashier	: NG CHUAN MIN
Sales Persor	: FATIN
Bill To	: THE PEAK QUARRY WORKS
Address	: .

Description	Qty	Price	Amount
000000111	1	193.00	193.00 SR
KINGS SAFETY SHOES KWD 805			

Qty: 1	Total Exclude GST:	193.00
	Total GST @6%:	0.00
	Total Inclusive GST:	193.00
	Round Amt:	0.00
	TOTAL:	193.00
	VISA CARD	193.00
	xxxxxxxxxxxx4318	
	Approval Code:000	

193.00

Goods Sold Are Not Returnable & Refundable
****Thank You. Please Come Again.****

Marie-Noël Lepage
30 mars 2023

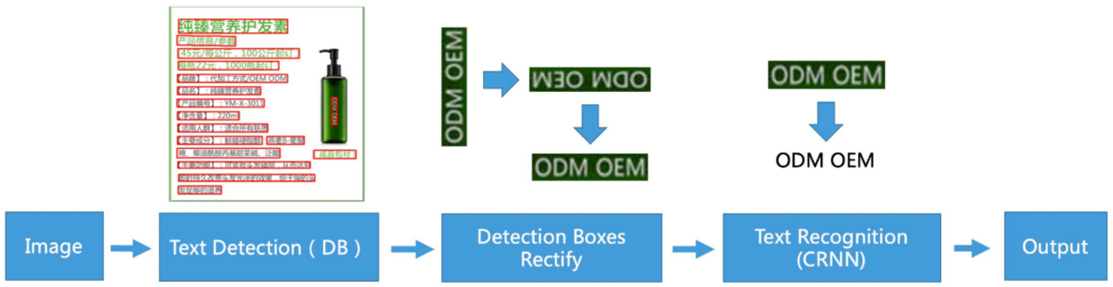
Problem Statement

Business documents (purchase orders, financial reports, letters, resume, invoice, ID cards, etc.) are critical to a company's efficiency and productivity. Understanding documents is a very challenging task due to the diversity of layout and formats, poor quality of scanned document image as well as the complexity of template structure but the information is usually presented in natural language. Many companies extract data from business documents through manual efforts that are time-consuming and expensive. To address these problems, using advanced deep learning are designed to automatically classify, extract, and structuralize information from documents.

Data Sources and Technique Used

The dataset used for this project was created for the ICDAR 2019 Robust Reading Challenge on Scanned Receipts OCR and Information Extraction (SROIE).[1] The dataset contains 973 scanned receipt written in English. It contains the pre-trained base model to extract information (for each receipt you have an .jpg file of the scanned receipt (image), a .txt file holding OCR information (box) and a .txt file holding the key information values (entities).

In case that our data are not pre-trained, we explore the machine learning model PaddleOCR[2] toolkits (PArallel Distributed Deep LEarning) that provide data annotation and synthesis tools support in more that 80 languages recognition. There are three major processing steps: character position detection, recognition of character orientation and correction character content recognition.

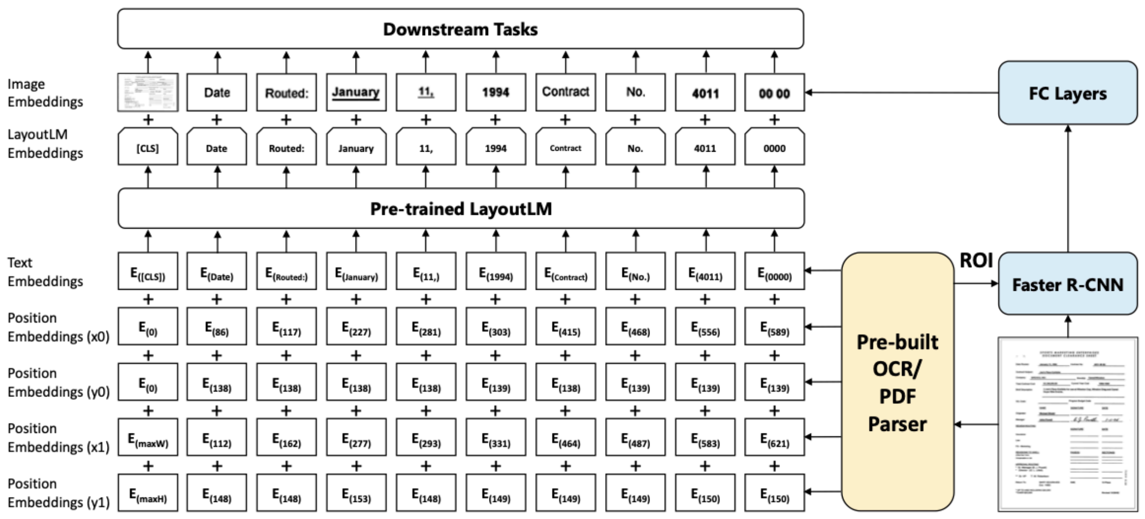


For assign labels correctly, we use the Hugging Face LayoutLM[3] model. It was one of the first models that archived success combining the pieces to create a singular model that performs labelling using positional information, text-based information, and image information. Inspired by the BERT (attention-based bidirectional language modelling approach), where input textual information is mainly represented by text embedding and position embeddings, LayouLM adds two types of input embeddings:

[1] https://rrc.cvc.uab.es/?ch=13
[2] https://github.com/PaddlePaddle/PaddleOCR
[3] https://huggingface.co/docs/transformers/model_doc/layoutlm

1. Based on the self-attention mechanism withing transformer, **embedding 2-D position** features into the language representation will better align the layout information with the semantic representation.

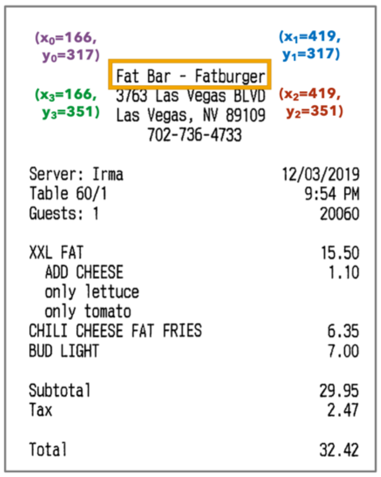
2. Combining the **image embedding** with traditional text representation can bring richer semantic representations to documents. It can capture some appearance such as font directions, types, and colors.



Preprocessing the Dataset and Fine Tune LayoutLM

Annotation of document:

The first thing we do is to extract the text-based information from the document and find their respective locations of recognize text for training our model. By location, we refer to something called a bounding box (a rectangle that encapsulates the piece of text on the page). The entities file represents the label you chose associate with the text recognition. With help of PaddleOCR, we can easily create the box and entities text files as the same format of the SROIE dataset.


(x_0=166, y_0=317)
(x_1=419, y_1=317)
(x_3=166, y_3=351)
(x_2=419, y_2=351)

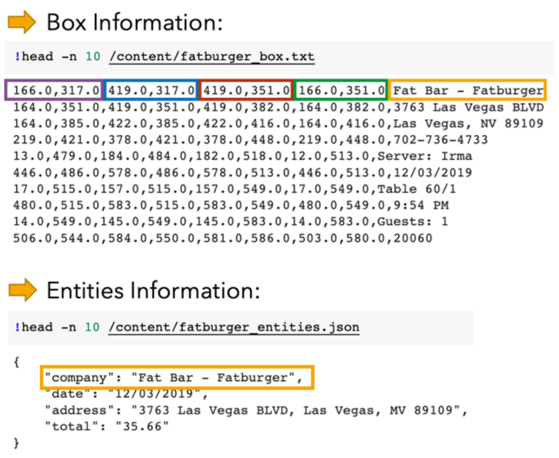
```
Fat Bar - Fatburger
3763 Las Vegas BLVD
Las Vegas, NV 89109
702-736-4733

Server: Irma                12/03/2019
Table 60/1                     9:54 PM
Guests: 1                        20060

XXL FAT                          15.50
  ADD CHEESE                      1.10
  only lettuce
  only tomato
CHILI CHEESE FAT FRIES            6.35
BUD LIGHT                         7.00

Subtotal                         29.95
Tax                               2.47

Total                            32.42
```


Box Information:

```
!head -n 10 /content/fatburger_box.txt
```

```
166.0,317.0,419.0,317.0,419.0,351.0,166.0,351.0,Fat Bar - Fatburger
164.0,351.0,419.0,351.0,419.0,382.0,164.0,382.0,3763 Las Vegas BLVD
164.0,385.0,422.0,385.0,422.0,416.0,164.0,416.0,Las Vegas, NV 89109
219.0,421.0,378.0,421.0,378.0,448.0,219.0,448.0,702-736-4733
13.0,479.0,184.0,484.0,182.0,518.0,12.0,513.0,Server: Irma
446.0,486.0,578.0,486.0,578.0,513.0,446.0,513.0,12/03/2019
17.0,515.0,157.0,515.0,157.0,549.0,17.0,549.0,Table 60/1
480.0,515.0,583.0,515.0,583.0,549.0,480.0,549.0,9:54 PM
14.0,549.0,145.0,549.0,145.0,583.0,14.0,583.0,Guests: 1
506.0,544.0,584.0,550.0,581.0,586.0,503.0,580.0,20060
```

Entities Information:

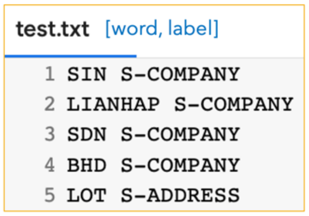
```
!head -n 10 /content/fatburger_entities.json
```

```
{
    "company": "Fat Bar - Fatburger",
    "date": "12/03/2019",
    "address": "3763 Las Vegas BLVD, Las Vegas, MV 89109",
    "total": "35.66"
}
```

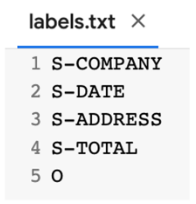
Data Preprocessing:

The dataset needs to be formatted in some way in files before the training and testing step. From the annotation step, we get our box file (text lines) and entities file (text labels). We need to reorganize them by assembling each line of text with its associated labels. Since all text must be labeled, we create an 'O' label for the undefined text. We match the label with the text line by checking the similarity according to a match higher than 80%. In addition, we assign total and date to only largest bounding boxes for no duplicate labels (a receipt could have only one item on it). Finally, we divide the lines of text into separate words (based on word length) with their own bounding boxes.

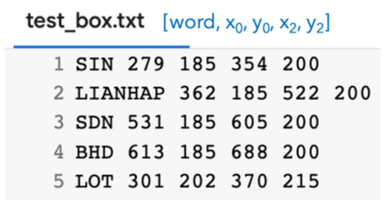
- **train.txt / test.txt:** This is the information that our model tries to predict. We use this file in the LayoutLM for calculate our performance metric on the model.
- **labels.txt:** Define the label using 'S-format'. All words must be labeled, and the 'O' represent each word not labeled in the annotation step.
- **train_box.txt / test_box.txt:** Bonding box should be in (x_0, y_0, x_2, y_2) format by word and normalized to scale of 0-1000.


test.txt [word, label]

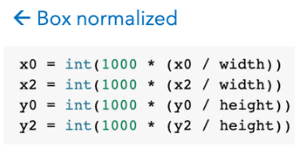
```
SIN S-COMPANY
LIANHAP S-COMPANY
SDN S-COMPANY
BHD S-COMPANY
LOT S-ADDRESS
```


labels.txt

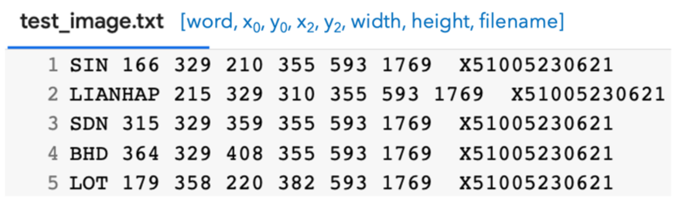
```
S-COMPANY
S-DATE
S-ADDRESS
S-TOTAL
O
```


test_box.txt [word, x_0, y_0, x_2, y_2]

```
SIN 279 185 354 200
LIANHAP 362 185 522 200
SDN 531 185 605 200
BHD 613 185 688 200
LOT 301 202 370 215
```


← Box normalized

```
x0 = int(1000 * (x0 / width))
x2 = int(1000 * (x2 / width))
y0 = int(1000 * (y0 / height))
y2 = int(1000 * (y2 / height))
```


test_image.txt [word, x_0, y_0, x_2, y_2, width, height, filename]

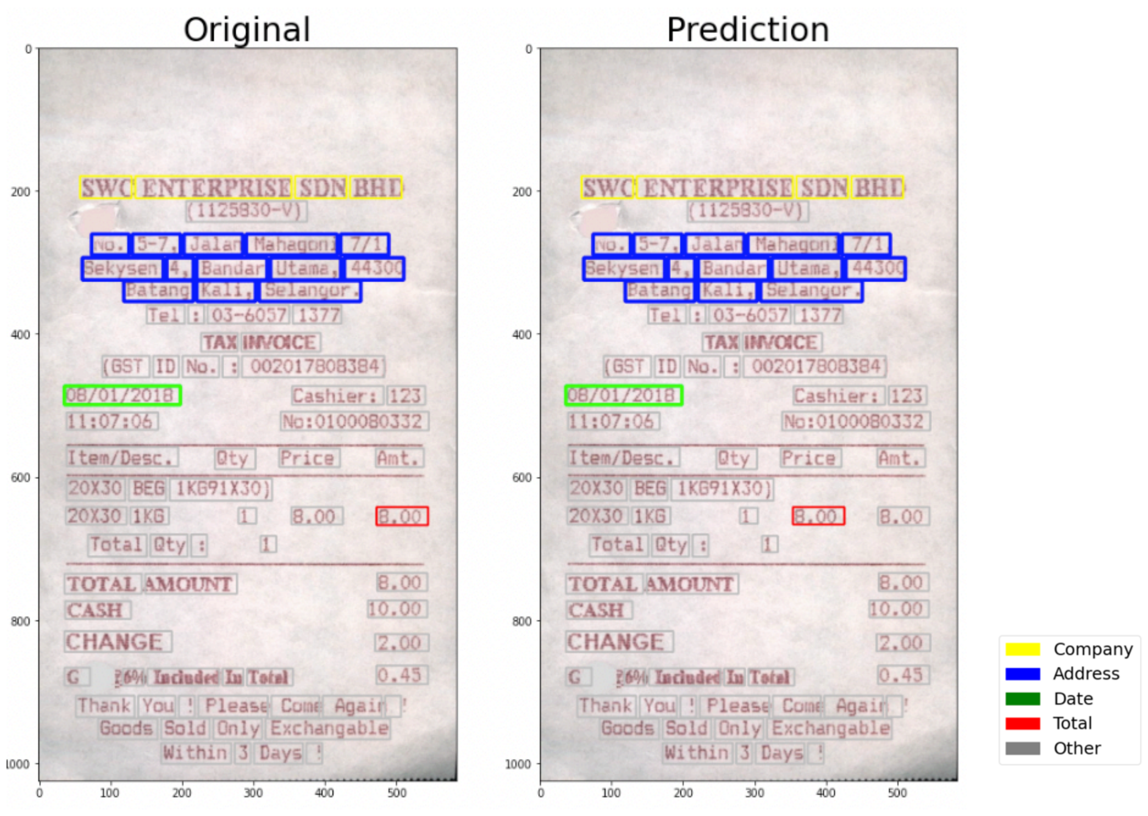
```
SIN 166 329 210 355 593 1769  X51005230621
LIANHAP 215 329 310 355 593 1769  X51005230621
SDN 315 329 359 355 593 1769  X51005230621
BHD 364 329 408 355 593 1769  X51005230621
LOT 179 358 220 382 593 1769  X51005230621
```

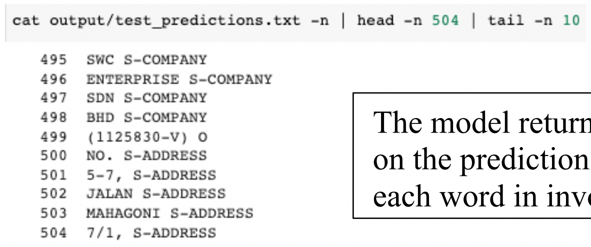
- **train_image.txt / test_image.txt:** All information that contain our document (word, bounding box, weight & height of the invoice and the filename.

Fine Tune LayoutLM:

As LayoutLM is a pre-trained model one won't need a large dataset to further train it. But it depends on the visual structure of your document. If you want to target a wide range of receipt formats you would need at least 200 images per targeted format to give you decent if not good performance. In our case, we have 626 invoices for the training step. We clone the LayoutLM GitHub project which contains the script and use the training and testing command related. These are the results after the training and testing on SROIE Dataset.

Metric	Score (%)	Definition
Loss	9.78	How many of the predictions may be not correct.
Precision	91.20	Ability of the classifier not to label as positive a sample that is negative.
Recall	96.17	Ability of the classifier to find all the positive samples.
F1-Score	93.62	Combining precision and recall. Described as the harmonic mean.





```
cat output/test_predictions.txt -n | head -n 504 | tail -n 10

   495	SWC S-COMPANY
   496	ENTERPRISE S-COMPANY
   497	SDN S-COMPANY
   498	BHD S-COMPANY
   499	(1125830-V) O
   500	NO. S-ADDRESS
   501	5-7, S-ADDRESS
   502	JALAN S-ADDRESS
   503	MAHAGONI S-ADDRESS
   504	7/1, S-ADDRESS
```

The model return a text file on the prediction of label for each word in invoices.

Conclusion

The model still gives a decent prediction and shows how powerful LayoutLM is. To improve accuracy, it's possible to adjust hyperparameter or train on more data depending on your needs. To extract further information like item row you would need to create appropriate labels for each item row using the 'S-format'. You would also need to create custom training data consisting of your newly created labels. Notes about the project:

- We can use other tools for annotation. As example, Tesseract, EasyOCR, UBIAI, AWS Textract or Google Cloud Vision. Label classification is done at the word level, so it is up to the OCR text extraction engine to ensure all words in a field are in a continuous sequence.
- Microsoft has released two news transformer model and should be improve in performance. The version 2 uses the detectron library to enable visual feature embeddings as well. The version 3 is the multi-modal transformer architecture that combines text and image embedding in a unified way. The main advantage of this approach is the reduction in parameters needed and overall lower computation.