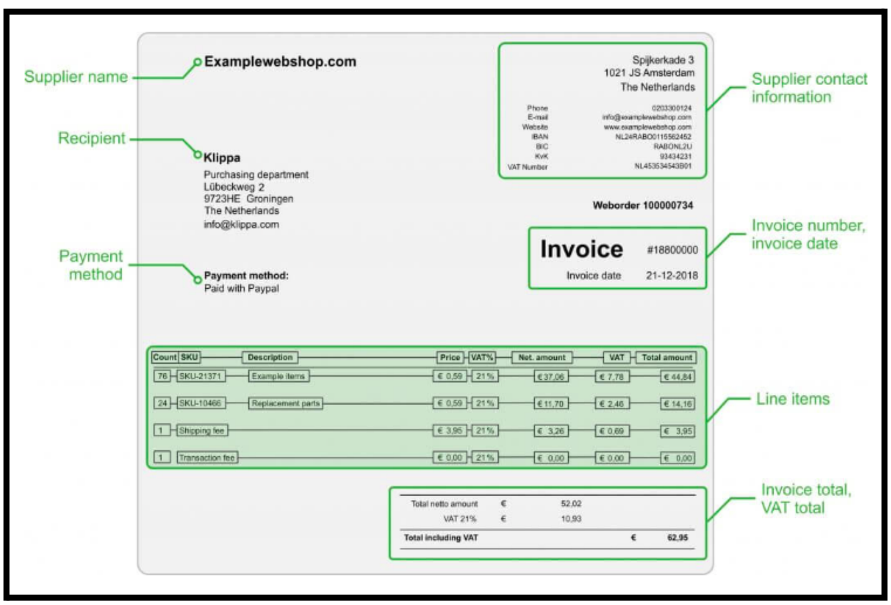
Tally Solutions Pvt. Ltd.

Document AI - Invoice Parser

Unstructured Data -> Structured Data

Introduction

With the growth of digitalization in all sorts of industries, companies want to automate most of their manual work, as manual work is prone to errors and is time consuming. One such case is the manual entry of form-like documents for further tasks, for example reading an invoice and filling entries like invoice date, seller name, buyer name, etc manually. This created a need for an algorithm that can automate this task by just taking invoice pdf as an input and outputting a json file containing all the extracted fields from that invoice.



Sample Output

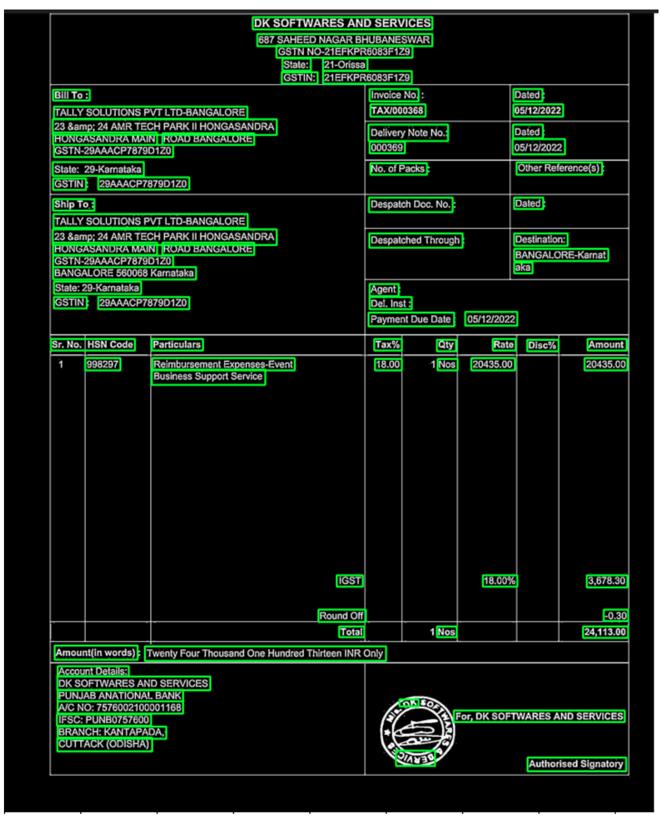
Methods

Several methods were tried and researched on, so as to compare the performance and accuracy of each approach in order to find the best approach.

Method 1 : Easy OCR and spacy

Easy OCR :

Easy OCR is a python's OCR library used for text extraction from images, we used this library to convert our image into a text format. Firstly, the images were preprocessed (Grayscale, Gaussian Blur, Binary Thresholding). Then, the Easy OCR was used on the preprocessed images to extract the text. This extracted text was further used in the NER (Named Entity Recognition) model.



DK SOFTWARES AND SERVICES
687 SAHEED NAGAR BHUBANESWAR
GSTN NO-21EFKPR6083F1Z9
State: 21-Orissa
GSTIN: 21EFKPR6083F1Z9

Bill To :
TALLY SOLUTIONS PVT LTD-BANGALORE
23 & 24 AMR TECH PARK II HONGASANDRA
HONGASANDRA MAIN ROAD BANGALORE
GSTN-29AAACP7879D1Z0
State: 29-Karnataka
GSTIN : 29AAACP7879D1Z0

Invoice No. : TAX/000368
Dated : 05/12/2022
Delivery Note No.: 000369
Dated : 05/12/2022
No. of Packs :
Other Reference(s) :

Ship To :
TALLY SOLUTIONS PVT LTD-BANGALORE
23 & 24 AMR TECH PARK II HONGASANDRA
HONGASANDRA MAIN ROAD BANGALORE
GSTN-29AAACP7879D1Z0
BANGALORE 560068 Karnataka
State: 29-Karnataka
GSTIN : 29AAACP7879D1Z0

Despatch Doc. No. :
Dated :
Despatched Through :
Destination: BANGALORE-Karnataka
Agent :
Del. Inst :
Payment Due Date : 05/12/2022

Sr. No.	HSN Code	Particulars	Tax%	Qty	Rate	Disc%	Amount
1	998297	Reimbursement Expenses-Event Business Support Service	18.00	1 Nos	20435.00		20435.00
		IGST			18.00%		3,678.30
		Round Off					-0.30
		Total		1 Nos			24,113.00

Amount(in words) : Twenty Four Thousand One Hundred Thirteen INR Only

Account Details:
DK SOFTWARES AND SERVICES
PUNJAB ANATIONAL BANK
A/C NO: 7576002100001168
IFSC: PUNB0757600
BRANCH: KANTAPADA,
CUTTACK (ODISHA)

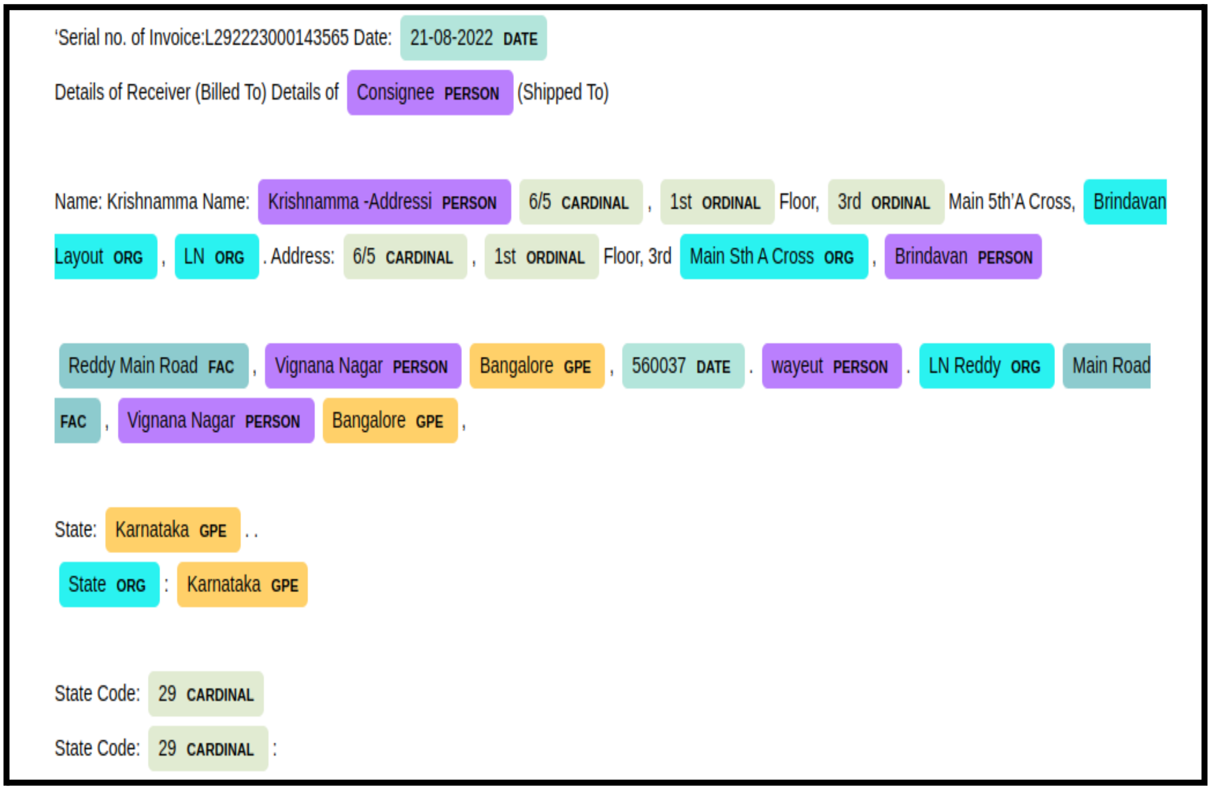
For, DK SOFTWARES AND SERVICES

Authorised Signatory

Easy OCR Output

Spacy :

Spacy is a python's library used for NER (Named Entity Recognition). Spacy takes text as an input, tokenizes the text and then predicts some common fields like, PERSON, ORG, DATE, etc from that text.

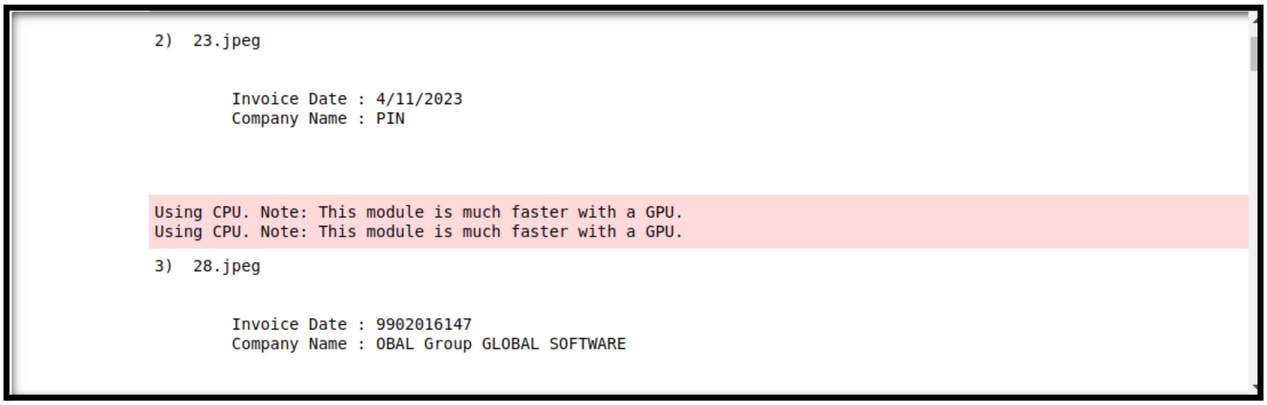


Spacy Output

Spacy has several pre-trained models to choose from like, small model, large model and the RoBERTa model. We chose the uncased models for small and large and compared the accuracy. Since the data in an invoice document is quite less, small model's accuracy came out to be slightly greater than that of the large model.

Results :

We tried and tested this model on some invoices to check the efficiency of this approach, it worked fine on many invoices for the fields like invoice date, but was not that effective for other name fields.



```
2)  23.jpeg

        Invoice Date : 4/11/2023
        Company Name : PIN

Using CPU. Note: This module is much faster with a GPU.
Using CPU. Note: This module is much faster with a GPU.
3)  28.jpeg

        Invoice Date : 9902016147
        Company Name : OBAL Group GLOBAL SOFTWARE
```

Spacy Inference

Findings :

- Easy OCR is a library that works better with the GPU and is a bit slow on using the CPU alone. It took around 15 seconds to extract the text from each image.
- Spacy is used in NLP tasks and works better if the text is semantic and holds a meaning, whereas in our use case, text is in the form of key : value pairs. Due to this reason, this approach failed in many invoices.
- Spacy gave a good result for the date field, but failed drastically on name fields like buyer name, seller name, etc.
- This approach is a purely NLP solution and does not take the positions of text into account.

Method 2 : Tesseract OCR

Tesseract OCR is Google's OCR engine and PyTesseract is the python's wrapper for this engine that can be used directly in our python code.

Tesseract OCR works similar to the Easy OCR, takes an image as an input and returns the output, but its output has a variety of fields and key information. We can extract the output in many forms like string, dictionary and dataframe. We extracted the text in the form of a dataframe. Output had various features like the text itself, bounding boxes, line number, word number, etc.

Out[75]:

	level	page_num	block_num	par_num	line_num	word_num	left	top	width	height	conf	text
4	5	1	1	1	1	1	654	125	44	26	90.456886	OK)
5	5	1	1	1	1	2	708	130	179	16	78.731796	SOFTWARES
6	5	1	1	1	1	3	896	125	67	26	78.731796	AND
7	5	1	1	1	1	4	974	130	140	16	95.575264	SERVICES
9	5	1	1	1	2	1	661	166	50	37	81.337814	684
...	...	...	...	...	...	...	...	...	...	...	...	...
127	5	1	9	1	3	1	142	1981	114	23	76.816223	BRANCH)
128	5	1	9	1	3	2	262	1981	158	26	66.789734	KANTAPADA)
130	5	1	9	1	4	1	138	2008	124	38	35.729332	CUTTACR)
131	5	1	9	1	4	2	271	2008	114	38	65.808868	(ODISHA)
135	5	1	10	1	1	1	111	43	1534	2071	95.000000	

86 rows × 12 columns

Tesseract Output

Now for testing this approach, we started with just a single field, InvoiceDate field. We pre processed this dataframe to extract all the rows having a datetime object in it.

- We first combined the text tokens extracted on the basis of block number and the distance between them.
- Then created n-grams for the combined texts.
- Used datetime parser to find fields having datetime objects in them.

Now that the fields having dates were extracted, it was required to add some neighbor information to train the model. For example if a date field has "invoice" written in its neighboring location, then it is surely the invoice date.

Firstly we took just a few neighbor fields like "invoice date", "date", "dated", "bill date" etc, and annotated them 1 or 0 based upon their presence in the top or left region of the concerned field.

Then this final dataset was given labeling as "isInvoiceDate" or "notInvoiceDate" manually. The final dataset had 36 rows and 19 columns.

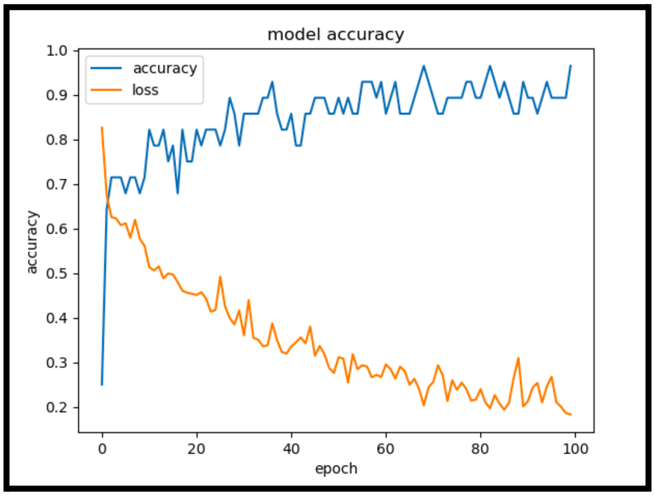
Now different model fittings were tested on this dataset for comparing performance.

Model 1 : Keras Sequential ANN Model

A simple ANN model was trained on this dataset for 100 epochs.

```
In [18]: model.summary()

Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 64)                1216

 dense_1 (Dense)             (None, 32)                2080

 dense_2 (Dense)             (None, 1)                 33

=================================================================
Total params: 3,329
Trainable params: 3,329
Non-trainable params: 0
_________________________________________________________________
```

Keras Model Summary

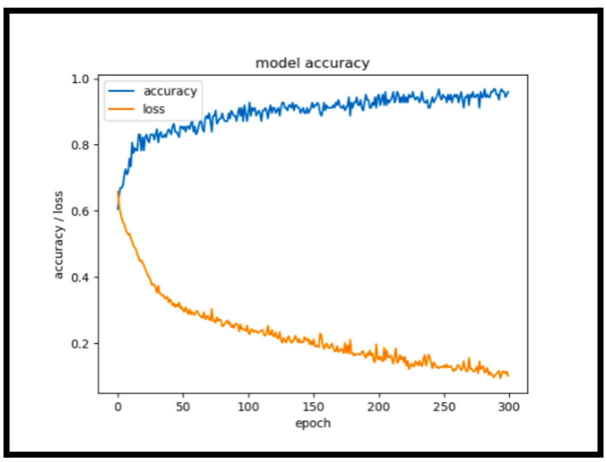


Keras Model Training

This model gave a testing accuracy of 87.5% and predicted 7 out of 8 testing images correctly. On increasing the dataset by 20 invoices and fine tuning the model, we were able to reach an accuracy of 88%

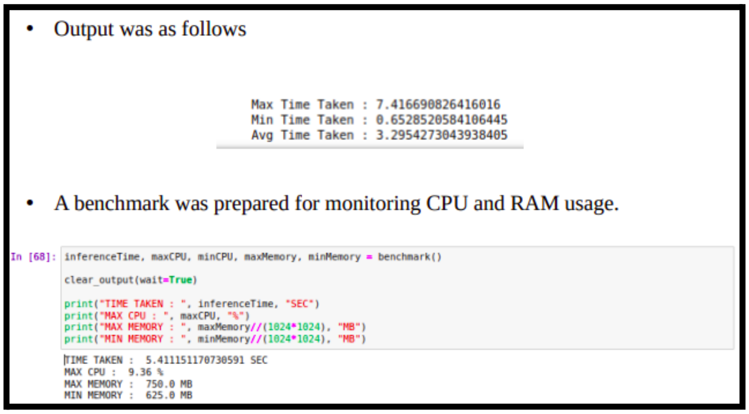
On testing the correlation between fields, we found out that neighbor fields were giving a really low correlation, so we changed neighbor extraction technique, and rather than taking its presence (1/0), we took its distance from the concerned field.

Finally the accuracy came out to be 93.55%



Keras Model Training

Now some performance benchmarks were performed on this model.



- Output was as follows

```
Max Time Taken : 7.416690826416016
Min Time Taken : 0.6528520584106445
Avg Time Taken : 3.2954273043938405
```

- A benchmark was prepared for monitoring CPU and RAM usage.

```
In [68]: inferenceTime, maxCPU, minCPU, maxMemory, minMemory = benchmark()

         clear_output(wait=True)

         print("TIME TAKEN : ", inferenceTime, "SEC")
         print("MAX CPU : ", maxCPU, "%")
         print("MAX MEMORY : ", maxMemory//(1024*1024), "MB")
         print("MIN MEMORY : ", minMemory//(1024*1024), "MB")

TIME TAKEN :  5.411151170730591 SEC
MAX CPU :  9.36 %
MAX MEMORY :  750.0 MB
MIN MEMORY :  625.0 MB
```

Keras Model Benchmark

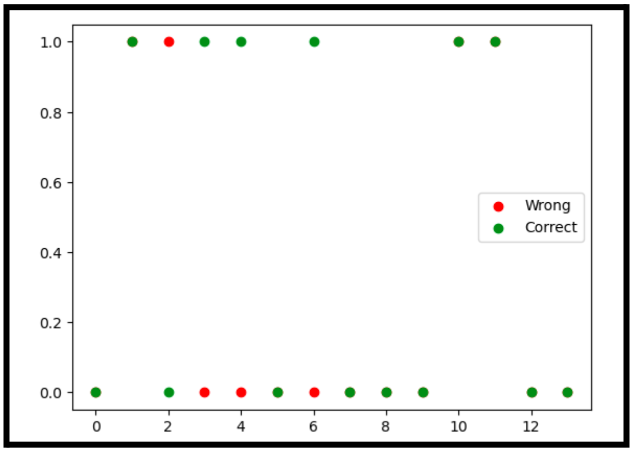
Model 2 : XGBOOST Model

XGBoost means extreme gradient boosting and it is an ensemble learning method that uses ensembles of decision trees to train the model. On applying the XGBoost model and comparing the accuracy with ANN model, we found that XGBoost was a clear cut winner in terms of accuracy. But the base model was still not generalizing good on the unseen data, so we performed some hyperparameter tuning using techniques like GridSearchCV but the generalization still remained bad. The problem was the low correlation between fields.

We tried adding more and more logical fields so as to improve correlation and hence the accuracy. We added a few context keywords like “invoiceDate” and used the distance of these keywords from the concerned field. Correlation improved but still it was not satisfactory. Now, rather than taking context keywords' distance, we took context keyword’s X and Y positions for training, fine tuned the XGBoost model and tried to improve the accuracy.

Since the dataset was really small, too many context keywords reduced the correlation significantly, so on trying with just two keywords, we achieved an 89% accuracy with just the base model, i.e, without hyperparameter tuning.

Now, as we were using many columns for neighbor fields, there was a need to combine these multiple columns and encode them into a single column for training. So we tried some encoding techniques and finally achieved a correlation of ~30% and an accuracy of 82%.



XGBoost Model Output

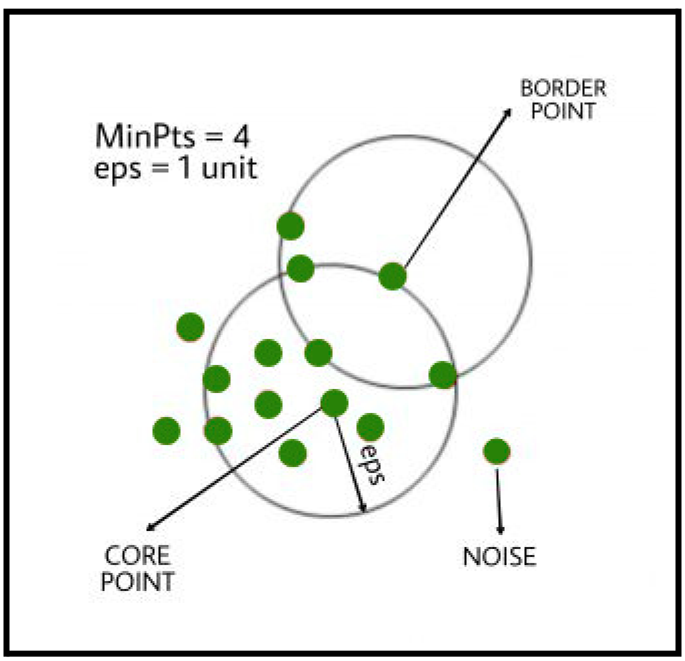
Findings :

- One of the major problems with this approach was the OCR. Tesseract OCR was only 50% efficient in extracting the text correctly, since tesseract OCR is better for semantic texts that hold a meaning.
- There was a need for a Zonal OCR technique which could read text in the form of zones.

Method 3 : Clustering

Clustering is an unsupervised learning mechanism that divides the data points into several groups based upon some parameters. There are several clustering algorithms like K-Means, K-Nearest-Neighbours, etc. But, these algorithms are good for spherical clusters and when the number of clusters to be made are already known. Since in our use case, each invoice can be different and is not template based, the number of clusters can differ in each invoice, so these algorithms won't work for us.

We here used an algorithm called DBSCAN (Density Based Spatial Clustering For Applications With Noise). In this algorithm the number of clusters need not to be defined and just the data points and two hyperparameters namely epsilon(eps) and minimum samples(min_samples) have to be provided for the clustering job.



DBSCAN Algorithm

Eps : Epsilon defines the distance after which the data points are classified to be other clusters. In simple words, all the points within the eps radius of a point are considered to be the same cluster.

Min-Samples : Min-Samples defines the number of data points required in an Eps radius to be classified as a cluster. All the data points which fail this property are known as noise.

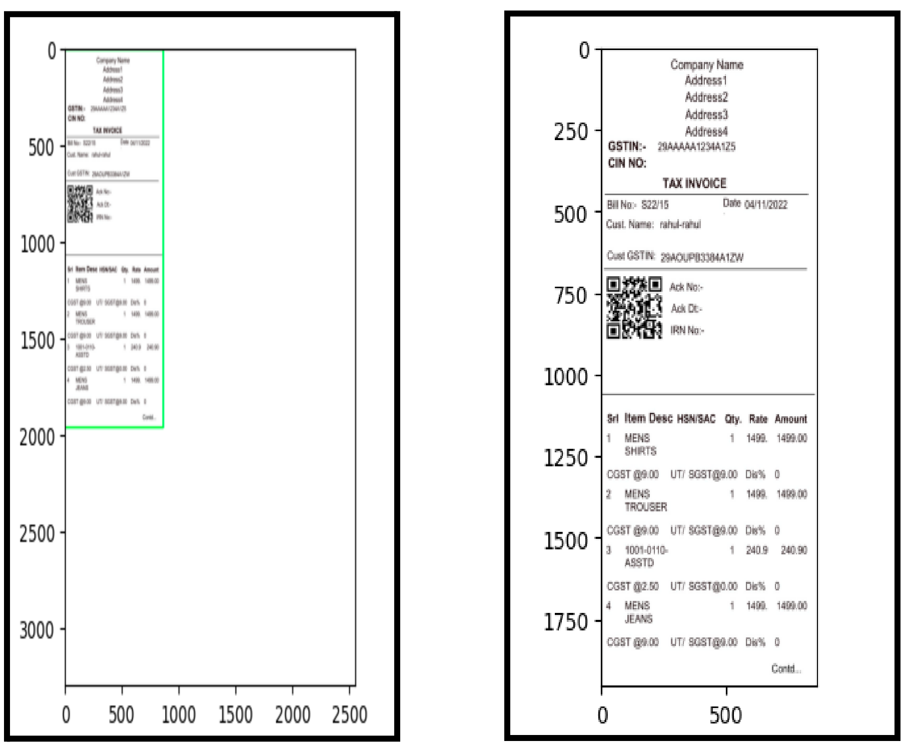
For using this algorithm, we pre processed the image so as to normalize the output by DBSCAN.

Image Pre Processing :

It included :

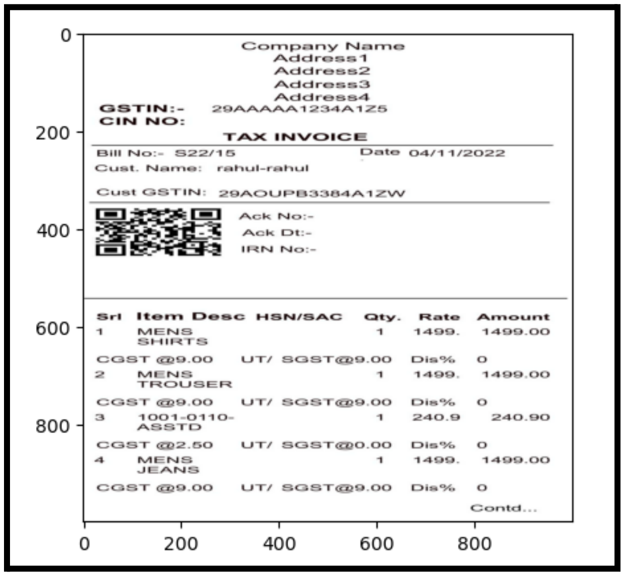
- Cropping the images for just the relevant area containing text.

  Example :



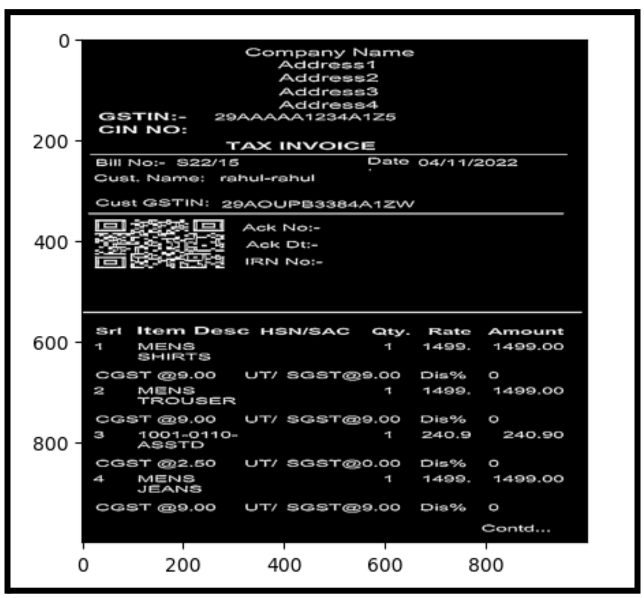
Before and After Cropping

- Converting images to a fixed size of 1000px X 1000px



After Resizing to 1000x1000

- Converting images to grayscale and adding blur and binary thresholding to increase contrast.



After applying Gray/Blur/Thresh

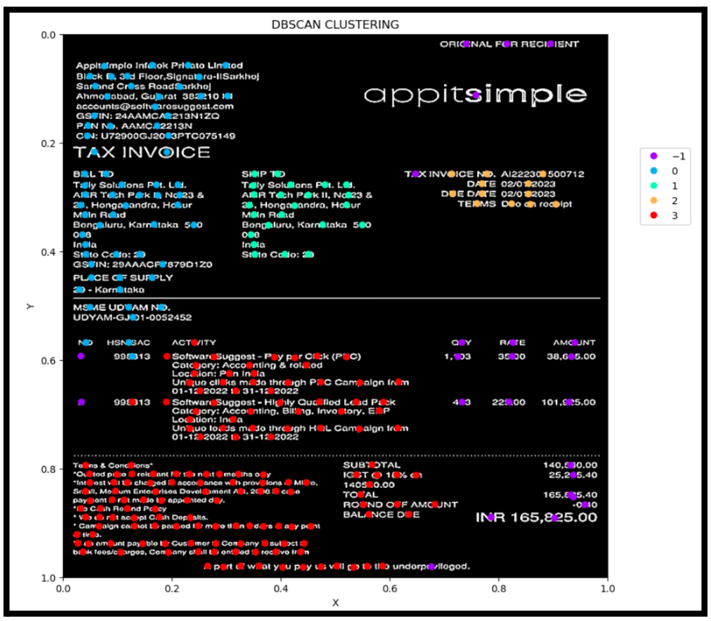
Clustering :

- These pre-processed images were passed through the tesseract OCR to extract all the text tokens from the image.
- The tesseract output was pre processed.
- DBSCAN clustering was applied with random parameters.

```
In [16]: clustering = DBSCAN(eps=0.09, min_samples=9).fit(XTrain)
```

DBSCAN Implementation Using SKLEARN

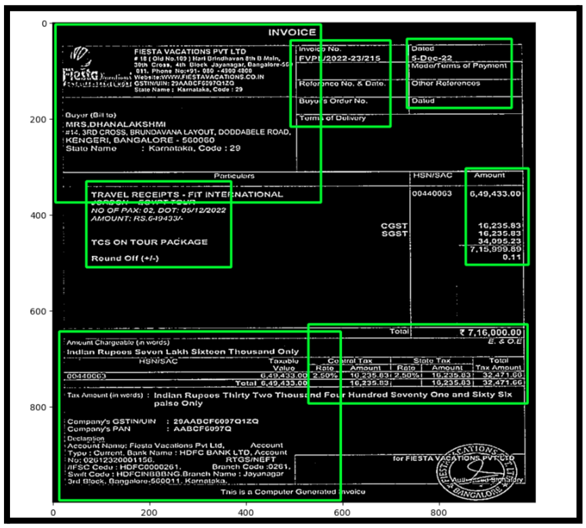
- After this, the DBSCAN clusters were overlapped on the original image to visualize the results.



DBSCAN Output

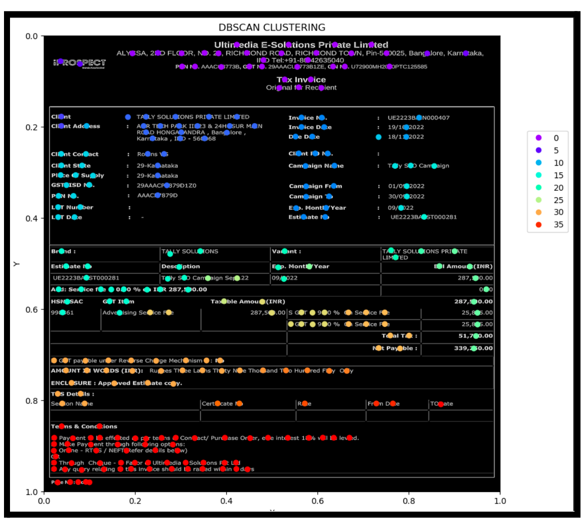
- DBSCAN divided the clusters in a really efficient way, but the same parameters didn't work fine on all images as each image had a different format.

- There was a need for some hyperparameter tuning for DBSCAN to fit each image accurately.
- Since, there are only two hyperparameters in DBSCAN, we used two simple for loops with a range of 5 points each to tune the parameters for each image seperately.
- After applying DBSCAN on 110 images, output was visualized using CV2.Rectangle function and the output was fair.



DBSCAN Clusters Visualized

- DBSCAN worked fine on many invoices but gave confounding results in some cases and divided key and value in different clusters.



DBSCAN Incorrect Output

- Now, as the output seemed satisfactory for some invoices, this was used to modify the tesseract output and the tokens were concatenated according to the cluster they belong to.
- If the data point belonged to the noise cluster, i.e, -1, it was simply ignored.
- The final dataset after this had 770 rows for 110 images.

	conf	text	x	y	imageName
0	62.857190	INVOICE FIESTA VAGATIONS PVT LTD Tinvoice ...	0.2810	0.1895	20.jpeg
1	53.489527	Tinvoice No. |EVPL/2022-23/215 Roference fio, ...	0.5965	0.1270	20.jpeg
2	53.916695	Gated 5-Doc-22 Mod = fodarTarms of Payment 'in...	0.8425	0.1060	20.jpeg
3	57.832790	Amount i 6 49,433.00 16,235.83 16,235.83 34 3 ...	0.9210	0.4045	20.jpeg
4	84.459252	TRAVEL RECEIPTS FIT YORDON + EGYPT TOUR NO OF ...	0.2200	0.4205	20.jpeg
...	...	...	...	...	...
765	69.189151	28-Sep-22 Mode/Teems of Payment Reference(s) N...	0.8425	0.1060	62.jpeg
766	60.873739	Total VATICURY 200.000!	0.9210	0.4045	62.jpeg
767	71.821769	Gescription of Servicos: Markating Exponse (To...	0.2200	0.4205	62.jpeg
768	72.512037	i Fotat Amount Chargeadie (in words) 'Omani Ri...	0.3055	0.8200	62.jpeg
769	45.959692	OMR 200.000! i _ &, OE)	0.7570	0.7115	62.jpeg

770 rows × 5 columns

Dataset Created By DBSCAN

- Now on analyzing the dataset, we realized that OCR did the job of reading the text but it misspelled most of the words maybe due to the image resizing to 1000px X 1000px.
- We removed the image resize step from the pre-processing and results showed that now the spellings were correct and clustering also improved slightly.
- Now, the final dataset consisted of 1917 rows and we annotated these rows into four classes, namely, invoiceDetails, sellerDetails, buyerDetails and amount.
- After annotation, we had to train a classification model which would predict the class in which each cluster lies.
- We used TFIDF vectorizer to convert the text to trainable features and used chi square similarity to find the most significant keywords for each class.

- Since our dataset was limited to our organization, rather than considering keywords like buyer and seller, it was taking “Tally”, “Solutions” as significant keywords.

```
Class----> amount:
     Most Correlated Unigrams are: total, amount, 00
     Most Correlated Bigrams are: hsn sac, amount in, in words


Class----> buyerDetails:
     Most Correlated Unigrams are: solutions, buyer, to
     Most Correlated Bigrams are: tally solutions, to tally, bill to


Class----> invoiceDetails:
     Most Correlated Unigrams are: 22, 2023, date
     Most Correlated Bigrams are: pvt ltd, amount in, in words


Class----> sellerDetails:
     Most Correlated Unigrams are: limited, company, india
     Most Correlated Bigrams are: amount in, in words, private limited
```

Most Significant Features For Each Class

Findings :

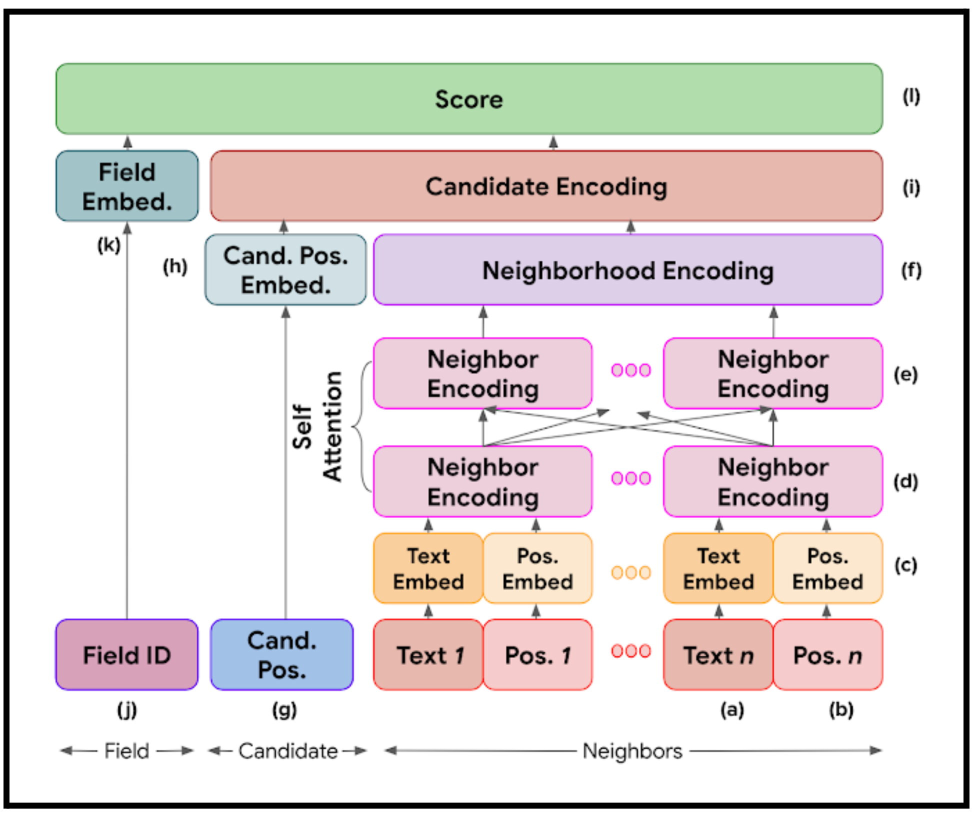
- DBSCAN algorithm uses distance to nearest neighbor for clustering and is better if the documents are template based, which in our use case is not the scenario and all the invoices have a different template/structure. Hence the DBSCAN output was not that accurate and keys and values lied in different clusters some times.
- Text could not be used for cluster classification as it was overfitting due to limited size and variance in the dataset.

Method 4 : Google's Representation Learning For Information Extraction From Form-Like Documents Implementation

Link to the original research paper :
https://ai.googleblog.com/2020/06/extracting-structured-data-from.html

This approach is quite similar to our approach in method 2 mentioned above. There are few changes in encoding techniques, feature selection for model training, and the final model for prediction.

In this Google used all the candidates for each field, encoded them along with the neighbor information and scored them against the ground truth (true value) encodings of each field.



Model Proposed By Google

Creating Data :

- For this experiment, first we started with just three fields, namely, InvoiceDate, InvoiceNumber and the TotalAmount.
- For capturing ground truth and creating a dataset, we used RoboFlow tool. We annotated 110 images using this, and exported our dataset in .csv format.

	filename	width	height	class	xmin	ymin	xmax	ymax
0	68.jpeg	2550	3300	InvoiceDate	1740	540	1975	625
1	68.jpeg	2550	3300	InvoiceNumber	300	860	690	940
2	68.jpeg	2550	3300	TotalAmount	1805	2405	2200	2500
3	56.jpeg	2550	3300	InvoiceNumber	168	408	389	455
4	56.jpeg	2550	3300	InvoiceDate	121	470	305	519
...	...	...	...	...	...	...	...	...
316	7.jpeg	2479	3500	InvoiceNumber	2025	650	2288	691
317	7.jpeg	2479	3500	TotalAmount	2087	217	2284	298
318	37.jpeg	2550	3300	InvoiceNumber	1871	167	2177	224
319	37.jpeg	2550	3300	InvoiceDate	2004	233	2273	278
320	37.jpeg	2550	3300	TotalAmount	1790	2205	2010	2300

321 rows × 8 columns

Annotated Dataset

- For extracting the text from each image, we used TesseractOCR and stored output of each of the 110 images in the form of a .json file.
- Now, we had to extract all the valid candidates for each of the fields in our schema. We used Regex for InvoiceNumber and Amount field and dateparser for the InvoiceDate field.


```
{'invoice_no': [{'text': '441TH',
   'x1': 1646,
   'y1': 163,
   'x2': 1767,
   'y2': 193},
  {'text': '4', 'x1': 1689, 'y1': 321, 'x2': 1711, 'y2': 351},
  {'text': '4', 'x1': 2145, 'y1': 321, 'x2': 2169, 'y2': 351},
  {'text': '3864542', 'x1': 2184, 'y1': 321, 'x2': 2351, 'y2': 351},
  {'text': '100484921000003', 'x1': 1131, 'y1': 577, 'x2': 1545, 'y2': 614},
  {'text': 'PCAP/INV/22-23/852', 'x1': 2100, 'y1': 718, 'x2': 2419, 'y2': 749},
  {'text': '1-Mar-23', 'x1': 2101, 'y1': 779, 'x2': 2267, 'y2': 810},
  {'text': 'PQE2C73457877A', 'x1': 2100, 'y1': 840, 'x2': 2421, 'y2': 871},
  {'text': '27-Feb-23', 'x1': 2099, 'y1': 901, 'x2': 2290, 'y2': 932},
  {'text': '100265405900003', 'x1': 296, 'y1': 939, 'x2': 636, 'y2': 970},
  {'text': 'PCAP/DN/22-23/1019', 'x1': 2100, 'y1': 962, 'x2': 2416, 'y2': 993},
  {'text': '7', 'x1': 2099, 'y1': 1024, 'x2': 2119, 'y2': 1053},
  {'text': 'IP13128GB-BLK-N', 'x1': 154, 'y1': 1201, 'x2': 497, 'y2': 1232},
  {'text': '13', 'x1': 719, 'y1': 1202, 'x2': 759, 'y2': 1232},
  {'text': '128GB', 'x1': 776, 'y1': 1201, 'x2': 899, 'y2': 1232},
  {'text': '100', 'x1': 1388, 'y1': 1202, 'x2': 1451, 'y2': 1232},
  {'text': '5', 'x1': 1827, 'y1': 1202, 'x2': 1847, 'y2': 1232},
  {'text': 'IP13128GB-BLU-N', 'x1': 153, 'y1': 1297, 'x2': 499, 'y2': 1328},
  {'text': '13', 'x1': 719, 'y1': 1297, 'x2': 759, 'y2': 1328},
  {'text': '128GB', 'x1': 776, 'y1': 1297, 'x2': 899, 'y2': 1328},
  {'text': '120', 'x1': 1388, 'y1': 1297, 'x2': 1451, 'y2': 1328},
```


RegEx Output

- Now, for each candidate we extracted its neighbor information, i.e, neighboring keyword's text, its "X" position and its "Y" position.


```
[[],
 [{'text': ['date'], 'X': 0.4183138362242839, 'Y': 0.059931506849315086}],
 [{'text': ['date'], 'X': 0.5865268253327955, 'Y': 0.07320205479452055}],
 [{'text': ['invoice'], 'X': 0.2045179507866074, 'Y': 0.012842465753424681},
  {'text': ['dated'], 'X': 0.018152480839047858, 'Y': 0.012842465753424681}],
 [{'text': ['payment'], 'X': 0.03146430012101642, 'Y': 0.007420091324200906}],
 [],
 [{'text': ['payment'], 'X': 0.11355385235982252, 'Y': 0.09817351598173524},
  {'text': ['due'], 'X': 0.14360629286002424, 'Y': 0.06720890410958913},
  {'text': ['date'], 'X': 0.03348124243646633, 'Y': 0.06720890410958913},
  {'text': ['delivery'],
   'X': 0.4945542557482856,
   'Y': 0.00042808219178080975}],
 [{'text': ['payment'], 'X': 0.2466720451795078, 'Y': 0.09731735159817362},
  {'text': ['date'], 'X': 0.03247277127874148‌6, 'Y': 0.09831621004566216},
  {'text': ['payment'], 'X': 0.1236385639370714, 'Y': 0.09018264840182655},
  {'text': ['due'], 'X': 0.013110125050423416, 'Y': 0.09118150684931514},
  {'text': ['due'], 'X': 0.27672448567970953, 'Y': 0.06635273972602751},
  {'text': ['date'], 'X': 0.16659943525615162, 'Y': 0.06635273972602751},
  {'text': ['payment'], 'X': 0.06171843485276318, 'Y': 0.06521118721461194}],
 [{'text': ['due'], 'X': 0.1393707139975796, 'Y': 0.07919520547945214},
  {'text': ['date'], 'X': 0.029245663574021696, 'Y': 0.07919520547945214},
  {'text': ['delivery'], 'X': 0.49031867688584096, 'Y': 0.012414383561643816}],
 [],
 [{'text': ['delivery'], 'X': 0.45018152480839047, 'Y': 0.03652968036529669}],
 [{'text': ['delivery'], 'X': 0.4497781363453005, 'Y': 0.04837328767123283‌4}],
```


Output Of Neighbor Extraction

- Now we created a word embedding table to encode each keyword into a meaningful numerical value. This was done by assigning same value to synonyms and similar sounding words.

```
vocab = ["invoice", "inv", "receipt", "bill", "order", "payment", "due", "date", "dated"]
emb = {
    "invoice" : 1,
    "inv" : 1,
    "bill" : 1,
    "receipt" : 1,
    "order" : 2,
    "payment" : 3,
    "due" : 4,
    "date" : 5,
    "dated" : 5
}
```

Word Embedding Table

- Now, we used PCA (Principal Component Analysis) to encode these three variables into a single variable for training.

```
[58]
from sklearn.decomposition import PCA
✓ 0.0s

[59]
pca = PCA(n_components=1)
✓ 0.0s

[60]
res = pca.fit_transform(xTrain)
✓ 0.0s
```

PCA

- We trained similar PCA models for candidate positions also and repeated the steps for all of the 110 images.
- Our final data looked like this.

	Unnamed: 0	text	CandidatePosition	NeighbourInformation
0	0	31-Dec-22	0.355992	0.269873
1	1	9902016147	0.369481	0.269891
2	2	Invoice	0.138290	0.269530
3	3	Desk	-0.244673	-0.493927
4	4	INTEGRATED	0.222155	-0.493927
5	5	+91	-0.124758	-0.493927
6	6	6661	-0.022596	-0.493927
7	7	7000	0.048244	-0.493927
8	8	18%|	0.449655	-0.493927
9	9	18%|	0.449655	-0.493927
10	10	_76,888.40|	0.680470	-0.493927
11	11	4,26,880.00 |	0.388924	-0.493927
12	12	76,838.40]	0.686578	-0.493927
13	13	DEC.'22	-0.444526	-0.493927
14	14	Desk	-0.369990	-0.493927
15	15	2%	-0.408592	-0.493927
16	16	6 7	0.614823	-0.493927

Dataset

Annotating Data :

- We used our RoboFlow annotations to annotate this dataset as a binary classifier with true invoice dates as 1 and other candidates as 0.

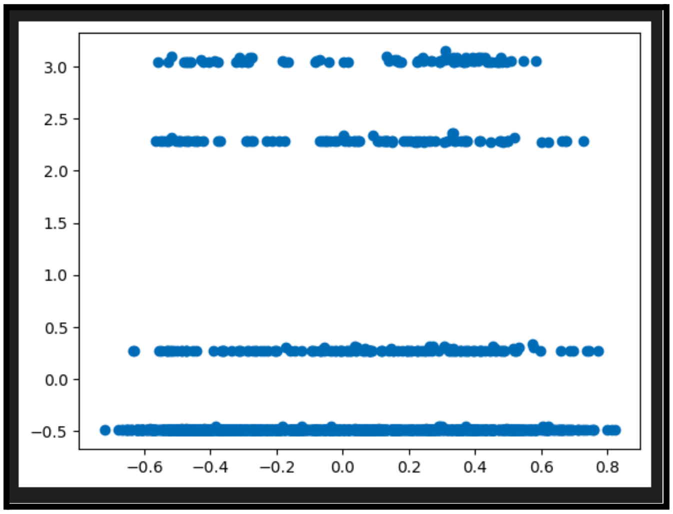
	text	CandidatePosition	NeighbourInformation	Output
0	$22	-0.641336	-0.493927	0
1	04/11/2022	-0.631070	0.269386	1
2	1499	-0.511586	0.269756	0
3	9.00 1499.00	-0.363099	0.270348	0
4	1499.00 MENS	-0.503532	-0.493927	0
5	1499	-0.501412	-0.493927	0
6	9.00 1499.00	-0.352926	-0.493927	0
7	1499.00 MENS	-0.493359	-0.493927	0
8	8901326000311	-0.606000	-0.493927	0
9	2.50 240.90	-0.344970	-0.493927	0
10	1499 9.00	-0.454457	-0.493927	0
11	9.00 1499.00	-0.332579	-0.493927	0
12	1499.00 5	-0.469936	-0.493927	0
13	5 201250239	-0.607681	-0.493927	0
14	9.00 899.00	-0.324669	-0.493927	0
15	4807.90	-0.306172	-0.493927	0
16	5636.90	-0.270322	0.270270	0
17	5636.90	-0.251935	-0.493927	0

Dataset After Annotation

- Now each of the images had one true value among all the candidates for each field.
- For experimental purposes we just started with a single field, i.e, invoiceDate field.

Processing Data :

- Now, on plotting the two input variables, i.e, “CandidatePosition” and “NeighbourInformation”, we found out that NeighbourInformation is broadly classified into 4 main categories.



Scatter Plot Of Input Variables

- So we used clustering to convert the NeighbouringInformation column into a categorical column (0, 1, 2, 3) and then used the get_dummies function to convert it into four columns.

	CandidatePosition	NeighbourInformation	Output	NeighbourClass_0	NeighbourClass_1	NeighbourClass_2	NeighbourClass_3
0	-0.486797	-0.475342	0	True	False	False	False
1	-0.473302	-0.475340	0	True	False	False	False
2	0.575232	0.330898	1	False	True	False	False
3	-0.535680	-0.493927	0	True	False	False	False
4	0.651722	-0.493927	0	True	False	False	False
...	...	...	...	...	...	...	...
1410	0.606355	-0.493927	0	True	False	False	False
1411	0.605394	-0.457813	0	True	False	False	False
1412	-0.467087	-0.493923	0	True	False	False	False
1413	-0.261925	0.269141	0	False	True	False	False
1414	0.032232	-0.493927	0	True	False	False	False

1415 rows × 7 columns

Final Dataset For Training

Model 1 :

- Now we trained a XGBoost classifier on this dataset.
- The best model achieved using GridSearchCV is shown below.

```
XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric='error', feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.08, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=6, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=10, n_jobs=None, num_parallel_tree=6,
              objective='binary:hinge', predictor=None, ...)
```

XGBoost model used

- Using this we achieved an accuracy of 89%.

```
Total :  283

True +ve :   244       93.85 %
True -ve :   8        34.78 %
False +ve :  16        6.15 %
False -ve    15        65.22 %


Accuracy :   89.05 %
```

Model Metrics

- But since our data was highly imbalanced in nature, accuracy can not be used as a perfect metric to evaluate this model. Our model was able to predict only 8 out of 23 images correctly.