



Let's Talk Digital Series #15

An Introduction to Optical Recognition Character (ORC)

## AN INTRODUCTION TO OPTICAL RECOGNITION CHARACTER

Some of our work involves manually reviewing and processing physical pages of documents, ranging from invoices to packing lists and insurance certificates, or to retrieve information from documents. It is a tedious process which can be automated by converting an image or a PDF (Portable Document Format) file into either a table or text. In this article, I will be introducing a few ways to retrieve text from PDFs and images.

For the first problem, I'll look at a summary of survey responses conducted by a news agency based in the US. Most PDF reports found online tend to be machine readable, so you can highlight parts of the report which contain the information you are after. It is usually easier to extract information from these documents as the Python code needed to perform this function is easy to write.

Specialty	Midwest (%)	Northeast (%)	South (%)	West (%)	Total (%)
Cancer	30.2	39.4	40.3	29.7	35.4
Diabetes & Endocrinology	34.5	20.5	28.3	13.9	24.4
Ear, Nose & Throat	16.7	33.3	29.0	39.0	29.9
Gastroenterology & GI Surgery	24.3	37.8	24.6	12.8	24.7
Geriatrics	15.2	15.6	13.3	13.8	14.5
Gynecology	25.8	21.2	28.3	13.5	23.0
Heart & Heart Surgery	36.1	43.6	18.8	32.4	30.6
Nephrology	25.7	21.2	17.9	17.1	19.9
Neurology & Neurosurgery	20.6	28.1	17.5	25.7	22.2
Ophthalmology	28.1	23.7	21.7	24.4	24.0
Orthopedics	25.7	25.0	19.7	21.3	22.2
Psychiatry	29.2	15.4	17.1	16.7	18.6
Pulmonology	13.8	16.2	32.7	31.6	25.2
Rehabilitation	21.2	28.2	32.7	12.5	24.2
Rheumatology	13.3	18.9	26.9	7.7	17.7
Urology	23.5	38.7	25.4	10.5	24.1
Overall Response Rate	24.2%	26.3%	24.8%	20.3%	24.0%

## Table 12. Nonmember Survey Response Rates by Region and Specialty, 2018

The image above shows an excerpt of the survey response rates by a hospital's departments. There are a few Python libraries available which can read text from PDF documents like PyPDF2, Textract, Apache Tika, pdfPlumber, and pdfMiner3. To read tables from PDF documents, I usually resort to a library called Tabula.

The raw result from Tabula is as follows:

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	9 Neurology & Neurosurgery	/ NaN	20.6		17.5	25 7	22.2		
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	12 Psychiatry	NaN	29.2		17 1	16 7	18.6		
	13 Pulmonology	v NaN	13.8		32 7	31.6	25.2		
	14 Rehabilitation	NaN	21.2		32.7	12.5	24.2		
	15 Rheumatology	NaN	13.3		26.9	7.7	17.7		
	16 Urology	v NaN	23.5		25.4	10.5	24.1		
	17 Overall Response Rate	e NaN	24.2%		24.8%	20.3%	24.0%		

After cleaning the table, a snapshot of the result should look like the following:

	Specialty	Midwest (%)	Northeast (%)	South (%)	West (%)	Total
1	Cancer	30.2	39.4	40.3	29.7	35.4
2	Diabetes & Endocrinology	34.5	20.5	28.3	13.9	24.4
3	Ear, Nose & Throat	16.7	33.3	29.0	39.0	29.9
4	Gastroenterology & GI Surgery	24.3	37.8	24.6	12.8	24.7
5	Geriatrics	15.2	15.6	13.3	13.8	14.5
6	Gynecology	25.8	21.2	28.3	13.5	23.0
7	Heart & Heart Surgery	36.1	43.6	18.8	32.4	30.6
8	Nephrology	25.7	21.2	17.9	17.1	19.9
9	Neurology & Neurosurgery	20.6	28.1	17.5	25.7	22.2
10	Ophthalmology	28.1	23.7	21.7	24.4	24.0
11	Orthopedics	25.7	25.0	19.7	21.3	22.2
12	Psychiatry	29.2	15.4	17.1	16.7	18.6
13	Pulmonology	13.8	16.2	32.7	31.6	25.2
14	Rehabilitation	21.2	28.2	32.7	12.5	24.2
15	Rheumatology	13.3	18.9	26.9	7.7	17.7
16	Urology	23.5	38.7	25.4	10.5	24.1
17	Overall Response Rate	24.2%	26.3%	24.8%	20.3%	24.0%

Comparing the cleaned output of Tabula and the table from the original document, , it can be observed that the results are similar. Once the Tabula output has been transformed into a table, it is easy to slice and dice the data as you see fit.

Sometimes, you do get scans of documents like the sample electricity bill to the right. The problem with scans of documents, or images of documents, is that it is slightly more difficult to get the information you would like. The reason is it is not possible to highlight any text on the image. These problems require the use of Optical Character Recognition (OCR). For this demonstration, I will be using Google Vision API's OCR.

OCR algorithms typically work like this:

- The AI isolates the area which have black inkblots against areas which do not. For areas which do have text, the algorithm draws boxes around the text. These boxes are called bounding boxes.
- The OCR algorithm then looks at individual inkblots to make out words or characters, and whether they are organized as a table or free-form text. It converts these texts into computer understandable text contained within the image.

The image with the bounding boxes is shown on the right.

The raw output of Google Vision API's OCR is as follows:

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Akhir\nRM\n526.85\n30.08.2018\nJenis Bacaan\nBacaan Sebenar\nTempoh Bil : 03.09.2018 - 03.10.2018 (31 Hari)\nTarif\nFaktor Prorata\ n:A: Kediaman\n1,00000\nBlok Tarif (KWh)\n200\n100\n300\n300\nBlok  $\label{eq:propaga} Prorata (kWh) \n200\n100\n300\n130\nKadar (RM) \n0.218\nAmaun (RM) \label{eq:prorata}$ n43.60\n33.40\n154.80\n70.98\n8\n0.334\n0.516\n0.546\nJumlah\n730\ n302.78\nTidak Kena\nST\nKena\nST\nKeterangan\nJumlah\nKegunaan kWh\nKegunaan\nkWh\n600\n130\n730\nRM\n231.80\n70.98\n302.78\ nKegunaan Bulan Semasa\nService Tax (66)\nKWTBB (1.6%)\nRM\n231.80\ n70.98\n302.78\n4.26\n4.84\n10\nCaj Semasa\nRM\n311.88\nBacaan Meter\nNo Meter\n\320\232egunaan\nUnit\nDahulu\nSemasa\n311201234\ n28470\n29200\n730\nkWh\nSubsidi 1.35 sen/kWh diblayai Kerajaan Persekutuan RM 10.61\nService Tax (ST) 6% bagi penggunaan Domestik melebihi 600 kWh\nBayaran melalui cek sah setelah penjelasan cek oleh bank\n\*220001234512000100012340000000031190\nAli bin Abu\ nE2SA - 201 Sek 3\nWangsa Maju\n53300\nWP Kuala Lumpur\nRM\n311.90\ nAras 17, Wisma TNB, No. 19. Jalan Timur, 46200 Petaling Jaya, Selangor.\nTENAGA NASIONAL BERHAD (200006), Nombor Datar ST W10-1608-31022372\n" bounding poly { . . .

The output can be converted into a table after some cleaning:

Blok	Tarif (KWh)	Blok Prorata (kWh)	Kadar (RM)	Amaun (RM)
1	200	200	0.218	43.60
2	100	100	0.334	33.40
3	300	300	0.516	154.80
4	300	130	0.546	70.98

After scanning or downloading files which contain the information you are looking for, this OCR algorithm can be applied to extract information from those files and feed this information to your systems by APIs. OCR works well if the document you are extracting information comes from files with a standard structure like ICs or any official forms, and the document should preferably be typed. For handwritten documents, the results of Google Vision API's OCR are likely to vary depending on the quality of the handwriting.



The full code for both demonstrations above can be accessed via the QR code on the right, or via the link here.



This article is part of the Digital Banking Learning Series, 'Let's Talk Digital', an initiative by the ABS Center for Digital Banking. It is written by industry practitioners and are aimed at educating the general public on the intricacies of digital applications in banking and other related industries, including the latest insights and trends of Digital Banking.

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