

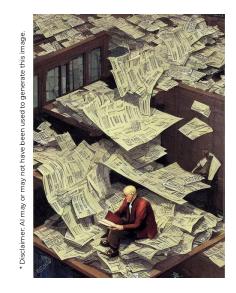
Teaching LLMs to Understand Business Documents

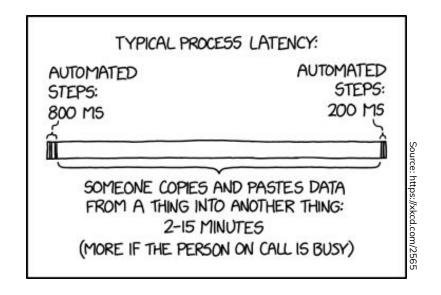
Al Days 2024 - 25/01/2024 - Tomáš Tunys (tomas.tunys@rossum.ai)



Context: Rossum Mission

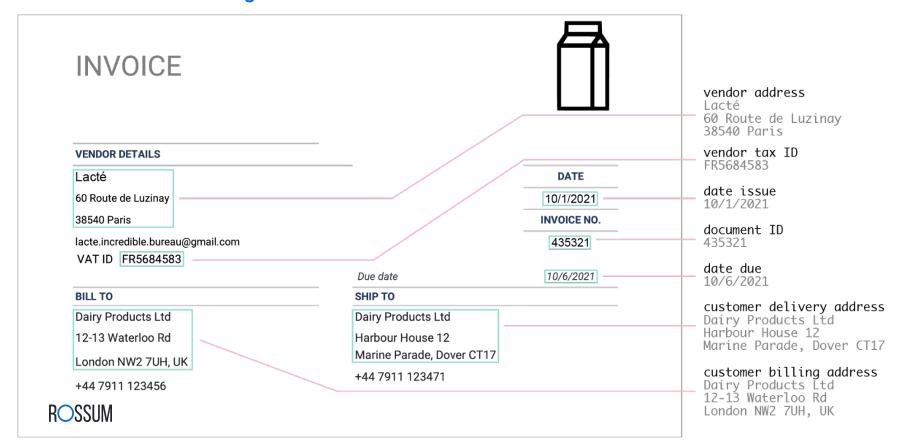
A person to handle a million transactions in a year.







Problem: Key Information Localisation & Extraction



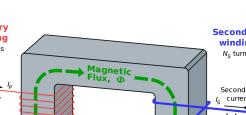
Problem: Key Information Localisation & Extraction





Approach: Our ML Pipeline to Solve KILE

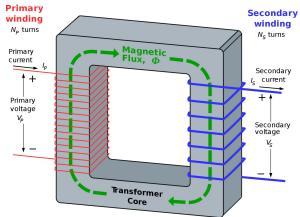
Step 1: OCR

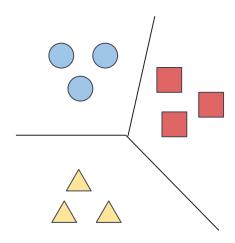


Step 2: Embedding

Step 3: Classification







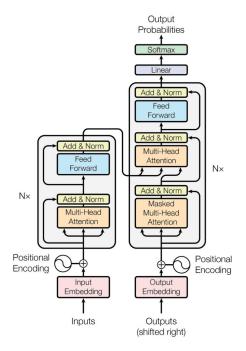


Approach: Our ML Pipeline to Solve KILE

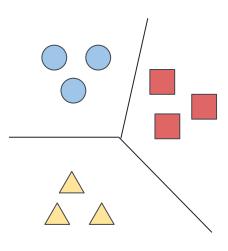
Step 1: OCR



Step 2: Embedding



Step 3: Classification





Step 1: OCR

"That's 40-year old problem that is solved"

- our beginnings at StartupYard (2016)



INVOICE



VENDOR DETAILS		
Lacté		DATE
60 Route de Luzinay		10/1/2021
38540 Paris		INVOICE NO.
lacte.incredible.bureau@gmail.com		435321
## ## ##	Due date	10/6/2021
BILL TO	SHIP TO	
Dairy Products Ltd	Dairy Products Ltd	
12-13 Waterloo Rd	Harbour House 12	
London NW2 7UH, UK	Marine Parade, Dover CT17	
+44 7911 123456	+44 7911 123471	

ITEM	DESCRIPTION	QTY	UNIT	TOTAL
001	SKU-582372	90 ltr	19.20	1 728.00
	Crème liquide semi épaisse légère 4%			
	Country of Origin: France	Ship Date: Jan 10. 2021		
002	SKU-989834	100 pcs	5.26	526.00
	Allergens: Lactose Country of Origin: France	Ship Date: Jan 10, 2021		
003	SKU-649293	70 pcs	4.80	336.00
	Beurre Doux Tendre			
	Country of Origin: France	Ship Date: Jan 10, 2021		



Step 1: OCR

Text Localisation: variant of DBNet (aithub:open-mmlab/mmocr)

Text Detection: variant of OCkRE (<u>aithub:rossumai/OCkRE</u>)

Training Data: Use PDFs + PDF parser (pypi:python-poppler)

Rossum history remark

 We used to crawl the Internet and scrape Uloz.to for PDF documents to train our first version of OCkRE.

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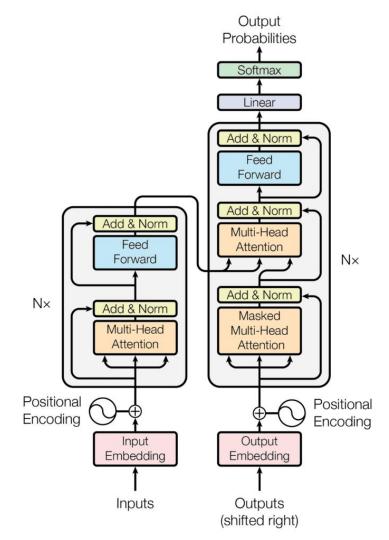


Step 2: Embedding

Turning Layout and Text information into vectors encoding semantic meaning.

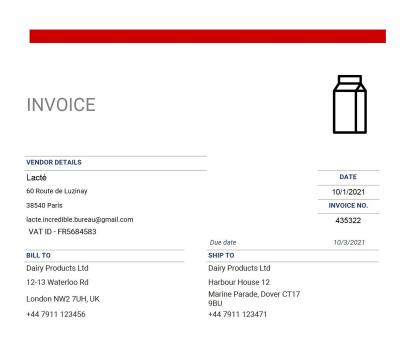
Variant of LLM inspired by models like <a href="https://hf:bert/hf:ber

- Encoder: "embedding quality control"
 - MLM pre-training in distribution documents.
 - Use layout (bounding boxes) during training.
- Decoder: "enhancing embeddings"
 - Its training is optional.
 - MVM filling the "blanks" in the covered parts of the document.





Step 2: LLM Pre-training via M(V)LM



DATASET

```
("INVOICE", [476, 295, 618, 326]),
("VENDOR", [475, 420, 533, 433]),
("DETAILS", [534, 418, 591, 434]),
("DATE", [1134, 456, 1175, 471]),
```



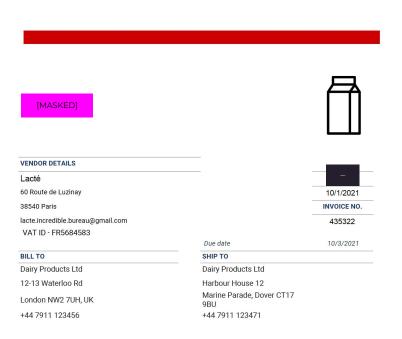








Step 2: LLM Pre-training via M(V)LM



DATASET - TRAINING BATCH

```
([MASKED], [476, 295, 618, 326]),
("VENDOR", [475, 420, 533, 433]),
("DETAILS", [???, ???, ???, ???]),
("DATE", [1134, 456, 1175, 471]),
```





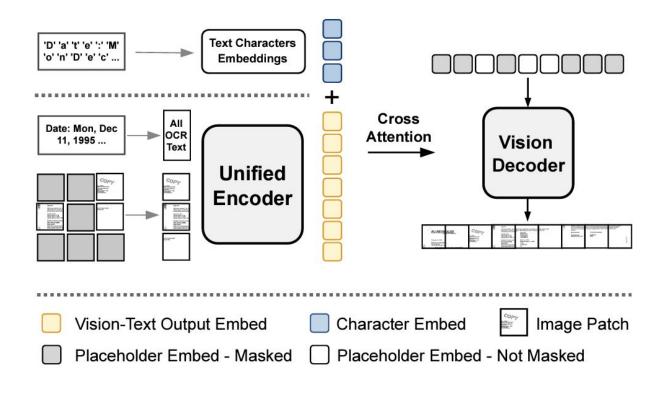




TRAINING OBJECTIVE: "Fill in the blanks"



Step 2: LLM Pre-training via M(V)LM





Step 3: Classification

LLM turns (localised) text into vectors encoding semantic meaning.

Here we can lean on vast collection of classic ML models: SVM, LogisticRegression, etc.

One of the go-to libraries in Python: <u>pypi:scikit-learn</u>

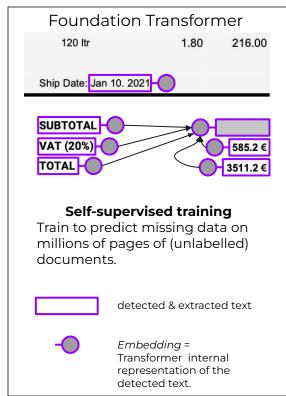
Dataset: human-annotated documents - e.g. Rossum UI (Slide 4)

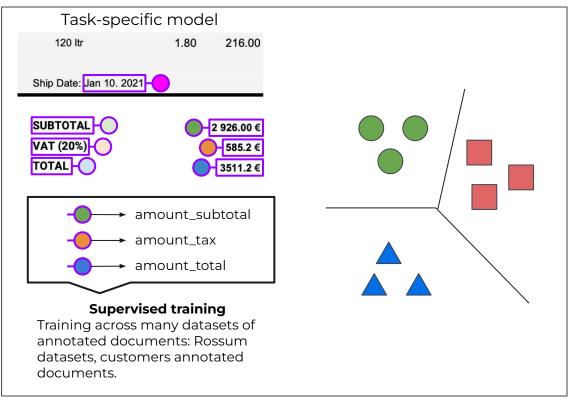
- Data points are (field type, location, text).
- This are turned using LLMs into "classical" dataset of 2-tuples:
 - (embedding vector, class/number representing the field type)

Pre-training and Classification can be trained jointly \rightarrow no need for separate model... has also other advantages.



Training: Self-supervised vs Supervised

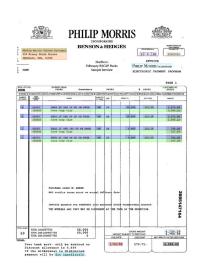






Reflection: Discriminative vs Generative Al

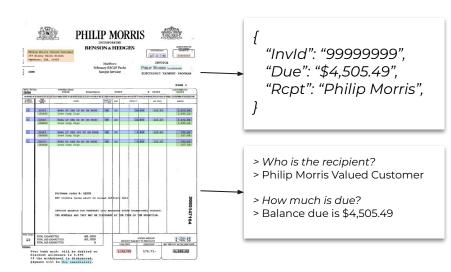
Reading an invoice is discriminative task:



"Specialist"

- Fixed to a particular task (e.g. set of fields)
- Efficient & effective
- Less prone to simple mistakes

Reading an invoice as generative task:



"Generalist"

- Creative (but can invent nonsense)
- Versatile, handles the unexpected
- Deeper understanding of reality

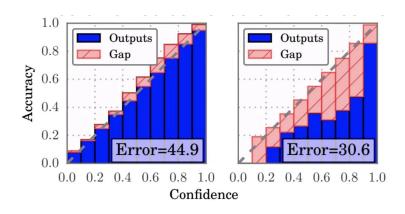


Ups... That's not All for the End-to-End Automation.

For practical purposes of any AI – the model needs to be able to express the level of confidence in its predictions.

One way to tackle this is to make the final model predictions calibrated.

Luckily, this can be reduced to a classical Al problem (see <u>Probability calibration</u> @scikit-learn)



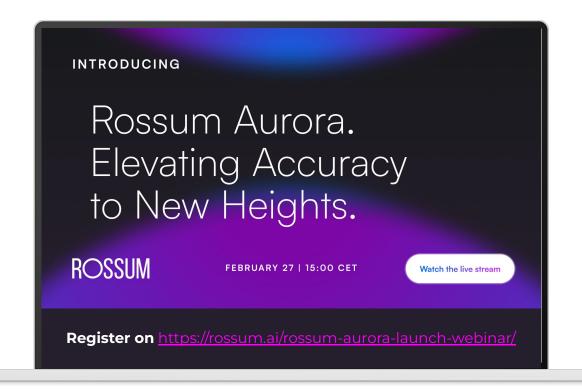


What are the Results / Impact of Rossum LLMs?

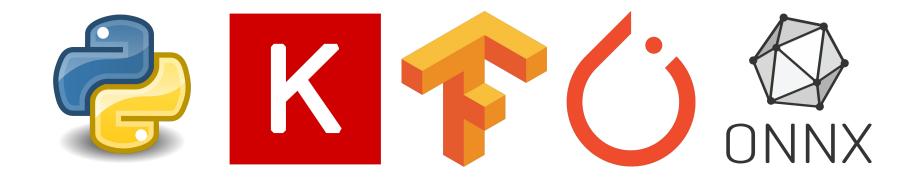




Coming Soon...









2017 - We Launch Rossum

"7GForce" - Our GPU "cluster":

- 4x GeForce GTX 1080Ti
- 3x GeForce GTX 1070
- 40 CPUs / 128 GB RAM

All technology up to the "LLM era" Rossum could have been built using this.

- Prioritisation of experiments would be the challenge.
- True to be told, we've been also using AWS a lot.





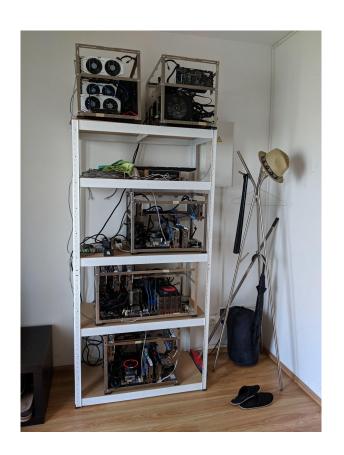
2018 - We grow and so does our compute.

Adding 4 "Ry-cka" to our "cluster":

- 12x GeForce GTX 1070
- 4x GeForce GTX 1080Ti
- 16 CPUs / 64 GB (each)

= 23 GPUs in total.

Has been enough for us until "recently" \rightarrow LLMs started.





2022 - 2023 - Latest upgrades to our cluster for the "LLM era":

Adding "Helena":

- 8x A100 GPUs
- 128 CPUs / 2T RAM

Adding "Sulla:

- 8x RTX 6000 Ada
- 128 CPUs / 2T RAM





Software & Hardware - when things go wrong:/



Takeaways

ML Pipeline for Key Information Localisation and Extraction

- 4 Stages: OCR → LLM → Classification → Calibration
- Can be built on top of open-source software and models:
 - Data can be a challenge for fine-tuning, not for pre-training of LLMs.
 - Compute can be a challenge:
 - But you can go far with "relatively" little.
 - Modern fine-tuning techniques exist (leverage the open-source!)
- How LLMs are trained and how it works.
- What are pros and cons of Discriminative vs Generative approaches.

What is possible when this is put in practice?

Come to see us at our <u>Rossum Aurora Product Launch</u>



Thank you

