# **Document Analysis in the time of LLMs**

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### **Talk Outline**

- Al Revolution
- Three Types of Document Analysis Systems
- Documents as Sources of Facts for LLMs

## REVOLUTION IN MACHINE LEARNING / AI

### LLMs / VLMs Have been Eating Machine Learning

- tasks that used to require extensive, specialized training...
- ... are now handled by foundation models
- ... or with minimal fine tuning

### **Big Changes over the Last Decade**

- broad, general models that work across many tasks and modalities
- very large scale unsupervised pretraining
- multitask training and multitask models
- efficient and simple fine-tuning on small datasets
- many problems solved with zero-shot or few-shot methods
- task specifications through natural language

## Zero/Few Shot with LLMs and VLMs

LLMs	VLMs
Named Entity Recognition (NER)	Object Recognition/Classification
Document Categorization	Object Detection
Sentiment Analysis	Scene Understanding
Text Summarization	Action Recognition
Machine Translation	•••
•••	

### **Example: Zero-Shot VLM Tasks**

- "Is there a dog in the image?"
- "What is the bounding box for the dog in the image?"
- "How many balls are there in the image?"
- "Is Marylin Monroe in the picture?"
- "Caption the picture."
- "Is the picture in focus?"

### **Example: Zero-Shot Document Classification**

```
prompt = """
### Instructions
You are given the text of the first page of a PDF document. Please extract the title,
author, year, and abstract. Then assign a category to the document
from the following list of categories:

    ocr: text recognition, layout analysis, page segmentation

    handwriting: handwriting recognition, handwriting synthesis, etc.

- scene-text: text recognition in natural images and scenes
... more categories ...
- other: anything else
You must return only a JSON format dictionary with fields of
title, author, abstract, year, and category. Your output
will be parsed by machine.
111111
classifier = OpenAIClient(prompt)
result = classifier.json query(text)
```

### Some Tasks Still Require Specialized Custom Models

(For now)

- Stereo -- two image input, specialized preprocessing
- Gaze Estimation -- high precision, specialized datasets
- Anomaly Detection -- specialized statistics
- 3D Pose Estimation for Articulated Objects -- complex structured outputs

• ...

## **Current State of OCR**

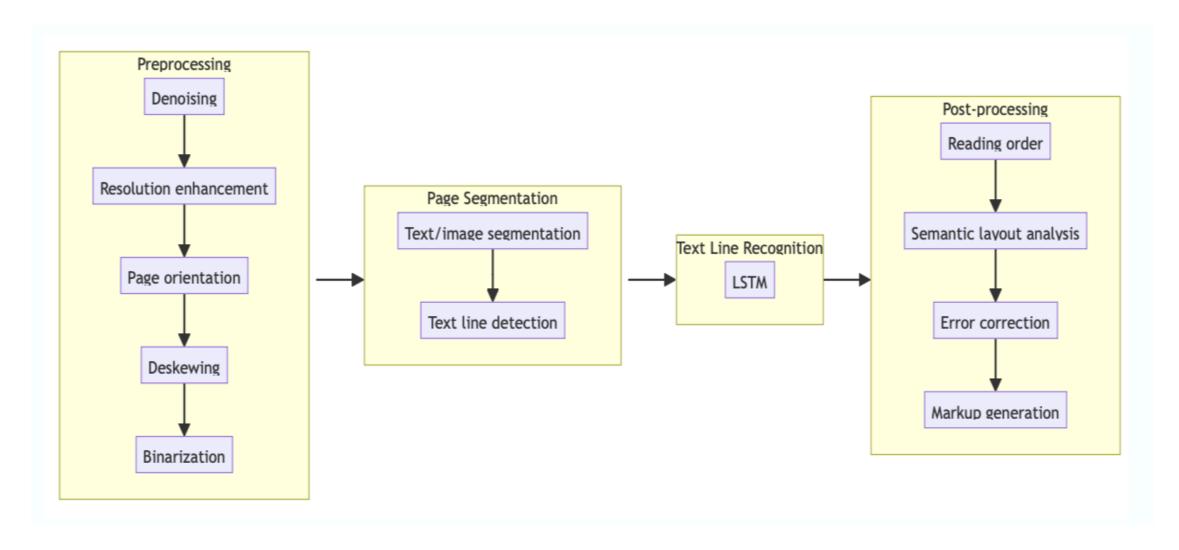
### **Users & Use Cases**

- Personal Library of Biomedical Researcher (>10<sup>6</sup> users)
  - Digital PDFs, some scanned.
  - Use LLMs for categorization, retrieval; not high accuracy.
  - Combo of OCR, pdf2text, and existing LLMs adequate.
- Financial Data Services Provider (<1000 users)</li>
  - Native digital PDFs; specialized layouts
  - Avoids image-based OCR, prefers text extraction
  - Mix of manual keying, OCR, digital formats; incremental improvements possible.

# **Users & Use Cases (2)**

- Large Academic/Non-Profit Archives (<100 users)</li>
  - Large diverse collections of scanned docs
  - Requires low error, high quality markupt, reading order.
  - Often used by academics interested in the details of the text.
  - Not currently well-served.
- Companies Training Foundation Models (<100 users)</li>
  - Large, scanned datasets for LLM training.
  - Unclear how much OCR errors affect LLM quality.

### "Traditional" OCR Pipeline

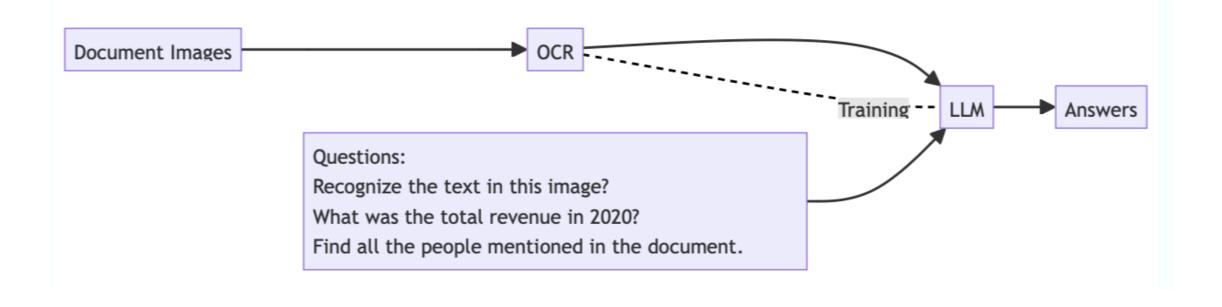


#### **OCR**

- high accuracy scanned-to-text conversion
- fast on high resolution images
- $\bullet < 0.5$  character error
- substantial problems with reading order, logical layout
- ideally, recover markup (LaTeX, etc.)

14

### OCR + LLM



#### OCR + LLM

- LLMs can solve many traditional retrieval and information extraction tasks
- LLMs are remarkably robust to OCR errors and layout errors
- LLMs also are good at OCR error correction ("correct the OCR errors in this text")
- combination of Traditional OCR + LLM works pretty well
- e.g. Tesseract + GPT-4o

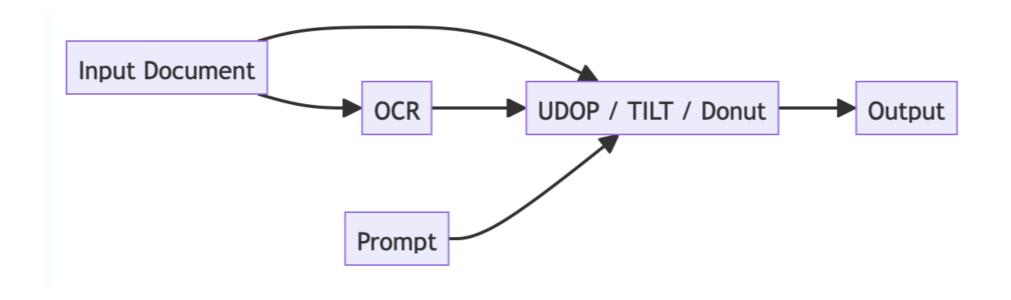
16

#### OCR + Multimodal Model

- substantial information is contained in the visual layout of documents
- traditional OCR systems are not very good at high level layout analysis

Examples: LayoutLMv3, UDOP, TILT, DocFormer, StrucText, ...

### **OCR + Multimodal Model**



18

#### OCR + Multimodal Model

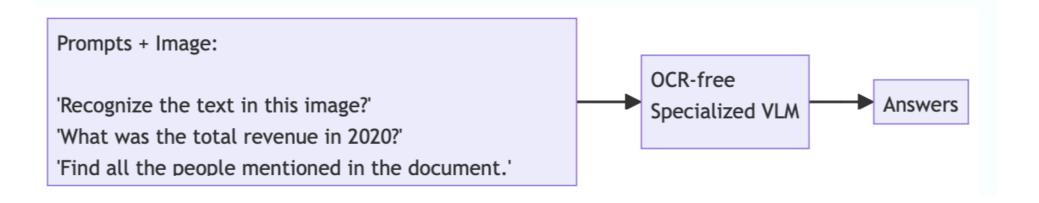
- OCR system can operate efficiently at high image resolutions
- multimodal model can handle layout analysis, reading order, etc.
- modularity of the system makes training, testing, and fine-tuning easier
- currently the most popular approach

### **OCR-Free Approaches**

- attempt to solve document understanding tasks without separate OCR step
- usually, a single transformer model performs both text recognition and layout analysis
- may perform full page recognition

Examples: Donut, DAN, TrOCR, ...

### **OCR-Free**



#### Transformer-Based "Traditional" OCR

Most "OCR-free" transformers cannot perform full OCR. A few can:

- TrOCR (CER 2.89% handwriting only)
- UDOP (CER 2.56%, IOU 91.62%)
- Nougat (CER 25.5%)
- Kosmos 2.5 (CER 9.2%, IOU 82.1%)

#### Note:

- These are not particularly good results by OCR standards.
- Unknown how much is due to language modeling and even memorization.

#### **Current Benchmarks and Leaderboards**

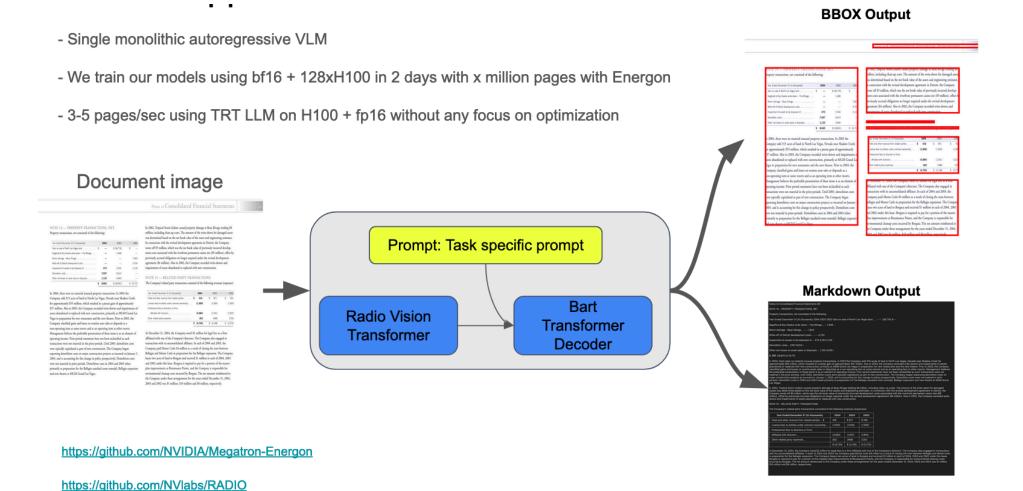
- text localization (receipts, etc)
- page segmentation and reading order (PubLayNet, PubTables-1M)
- visual question answering (VQA, DocVQA)
- key information extraction (KIE on SROIE)
- no widely used end-to-end OCR benchmarks

#### **NVIDIA OCR Efforts and Foundation Models**

#### Ambitious all-in-one effort:

- VLMs that handle vision, scenes, and documents
- prompted responses
- document capabilities:
  - high accuracy image-to-text for books, articles
  - outputs logical and physical markup (headers, footnotes, etc.)
  - handles math and other special content
- massive training and data management effort due to generality of model

#### **NVIDIA Architecture**



### **NVIDIA Results**

Internal Test Set		
	Word Error Rate	Passed Pages (F1 > 0.75)
ECLAIR	6.0%	99.1%
(commercial hosted OCR)	8.4%	96.4%
Kosmos-2.5	15.9%	91.2%
PyMuPDF	22.9%	94.75%

### What's Missing

- Need better end-to-end OCR benchmarks, not just task-specific benchmarks.
- Need more dense and diverse annotated dataset and benchmarks with complete annotation
- Better coverage (training+benchmarks) of mathematical equations, chemistry, etc.
- More diversity: different set of layout, languages, fonts, etc.
- Better coverage of uncommon layouts.

#### **OCR Future**

Two different OCR approaches:

- High performance self-contained OCR as input to LLMs and multimodal models
- Multimodal models that perform basic OCR/layout and invoke specialized agents.

Both will likely co-exist for some time.

## What do we need OCR for?

#### What do we need OCR for?

- largely already converted (e.g. Gutenberg)
  - important pre-1924 books
  - important scientific papers
- good alternatives to OCR / good custom solutions
  - business, legal, government communications
  - scene text (camera based translation, self-driving cars, etc.)
- largely available in digital format
  - open source textbooks and other publications
  - scientific publications (tagged PDF/A will have large impact)

### **Objective?**

We are trying to translate texts into facts

31

### Types of Tasks involved in LLM Answers

- knowledge of facts ("Lincoln was president")
- knowledge of meta-facts ("this fact is true according to...")
- ability to reason ("Lincoln was a US citizen because he was president.")
  - reasoning can be imitated with factual knowledge
- ability to recall verbating ("please quote ...")

### MMLU Examples of Multiple-Choice Questions

#### **Biology Example: (fact, knowledge)**

What is the powerhouse of the cell?

(A) Nucleus (B) Mitochondria (C) Ribosome (D) Endoplasmic Reticulum

#### **Mathematics Example: (inference)**

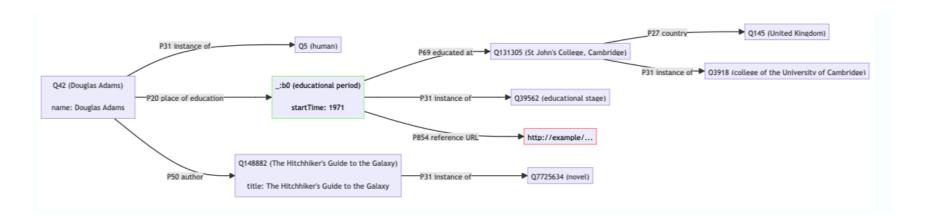
If 4 daps = 7 yaps, and 5 yaps = 3 baps, how many daps equal 42 baps?

(A) 28 (B) 21 (C) 40 (D) 30

#### What do Facts Look Like?

```
wikidata_item:
 item id: Q42 # Unique identifier
 labels: "Douglas Adams" # Main name
 descriptions: "English writer and humorist" # Short description
  aliases: ["Douglas Noël Adams"] # Alternative names
  sitelinks: ["https://en.wikipedia.org/wiki/Douglas Adams"] # Wikipedia link
  statements:
    - property: Height
      property id: P2048
      value: "185 cm" # Simple property example
    - property: Educated at
      property_id: P69
      value: {item: "St John's College, Cambridge", item id: Q691283} # Statement pointing to another Q item
      qualifiers:
        - {qualifier: Start date, qualifier_id: P580, value: 1971}
       - {qualifier: End date, qualifier id: P582, value: 1974}
      references:
        - {reference_property: Reference URL, reference_property_id: P854, value: "https://source.link"} # Reference URL
```

### What do Facts Look Like?



#### What do Facts Look Like?

```
<"Q42 (Douglas Adams)", "name", "Douglas Adams">
<"Q42 (Douglas Adams)", "alias", "Douglas Noel Adams">
<"Q42 (Douglas Adams)", "P31 (instance of)", "Q5 (human)">
<"Q42 (Douglas Adams)", "P22 (father)", "_:b0 (educational period)">
<"Q42 (Douglas Adams)", "P50 (author)", "Q148882 (The Hitchhiker's Guide to the Galaxy)">
<" :b0 (educational period)", "startTime", "1971">
<"_:b0 (educational period)", "endTime", "1974">
<"_:b0 (educational period)", "P69 (educated at)", "Q131305 (St John's College, Cambridge)">
<"_:b0 (educational period)", "P31 (instance of)", "Q39562 (educational stage)">
<" :b0 (educational period)", "P854 (reference URL)", "http://example/...">
<"Q131305 (St John's College, Cambridge)", "P27 (country)", "Q145 (United Kingdom)">
<"Q131305 (St John's College, Cambridge)", "P31 (instance of)", "Q3918 (college of the University of Cambridge)">
<"Q148882 (The Hitchhiker's Guide to the Galaxy)", "title", "The Hitchhiker's Guide to the Galaxy">
<"Q148882 (The Hitchhiker's Guide to the Galaxy)", "firstPublished", "1979">
<"0148882 (The Hitchhiker's Guide to the Galaxy)", "P31 (instance of)", "07725634 (novel)">
```

#### What do facts look like?

Douglas Adams, also known as Douglas Noel Adams, was a human. He authored the novel "The Hitchhiker's Guide to the Galaxy", first published in 1979. From 1971 to 1974, he was educated at St John's College, Cambridge, which is a college of the University of Cambridge in the United Kingdom.

### Classical Problems with Symbolic Al

- term resolution
  - "Douglas Adams" "Douglas Noel Adams"
- disambiguation
  - "John Smith (actor)" vs "John Smith (politician)"
- ontology mapping
  - Wikidata "educated at" vs. DBpedia "alma mater"
- LLMs are good at resolving these problems

38

#### **Facts and Documents**

Documents can be understood as collections of facts:

- simple statements of facts ("Hydrogen is the lightest element")
- context-dependent facts ("Lincoln was president from 1861 to 1865")
- meta-facts ("According to ... Lincoln was president from 1861 to 1865")
- textual facts ("'Shall I compare thee to a summer's day?' is the first line of a sonnet by Shakespeare")

#### A Statistical Model of Facts

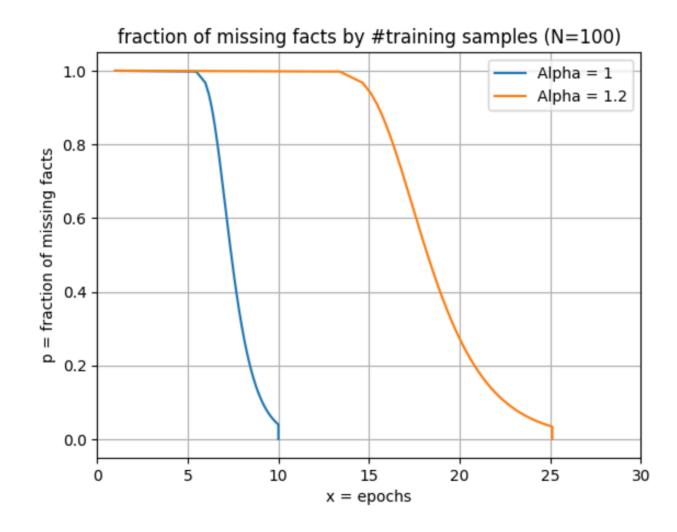
#### Model:

- facts are distributed across texts in a power law distribution
- ullet LLMs need to be exposed to each fact approximately k times to learn it
- performance on fact-based benchmarks reflects the percentage of facts learned

#### Prediction:

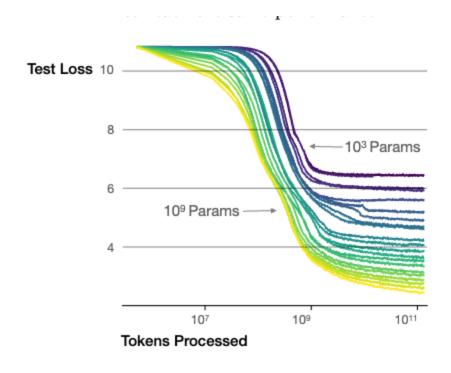
• how long does it take to learn x% of facts in a corpus?

### **Predictions of Learning Behavior**



### **Actual Observations**

Scaling Laws for Neural Language Models



Kaplan et al. 2021

#### **Observations**

- learning itself is a power law process
- the exponent of the power law is critical in determining learning time
- we can potentially achieve great improvements by achieving a more uniform distribution of facts

43

### **Approaches to Achieving Uniform Fact Distribution**

- machine learning approaches
  - use umbrella sampling of documents
  - use boosting
- data driven approaches
  - careful manual selection of training data (e.g., textbooks)
  - small LLMs + utilize facts directly during inference
  - train directly on facts instead of documents

# **Summary**

#### State of OCR

- Traditional OCR: high text accuracy, layout issues
- Three approaches: OCR+LLM, OCR+VLM, OCR-free
- Likely will continue to co-exist: different strengths/weaknesses.
- High performance image-to-markup desirable for many applications.
- Need:
  - Improve coverage: diverse layouts, math, formulas, etc.
  - Better end-to-end OCR benchmarks

### State of Knowledge and Reasoning

- LLMs learn and reason from facts
- LLMs are primarily benchmarked on facts and inference
- Making facts explicit helps with acquisition, testing, reasoning
- Power law governs learning efficiency
- Scaling laws crucial for fact acquisition
- Uniform fact distribution potentially improves learning