

# OLMOCR: Unlocking Trillions of Tokens in PDFs with Vision Language Models

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## Abstract

PDF documents offer trillions of novel, high-quality tokens for language model training, but their diverse formats and layouts complicate content extraction. Traditional open source tools yield lower quality results than vision language models (VLMs), yet the best VLMs are costly (e.g., over \$6,240 per million PDF pages for GPT-4o) or inaccessible when working with proprietary documents. We present OLMOCR, an open-source toolkit for converting PDFs into clean, linearized plain text in natural reading order while preserving structure such as sections, tables, and equations. Our toolkit uses a fine-tuned 7B VLM trained on 260,000 pages from over 100,000 varied PDFs, including graphics, handwritten text, and poor scans. OLMOCR is optimized for large-scale batch processing, converting a million pages for only \$176. We find OLMOCR outperforms even top VLMs including GPT-4o, Gemini Flash 2 and Qwen-2.5-VL on OLMOCR-BENCH, a curated set of 1,400 challenging PDFs with fine-grained unit tests that remain challenging even for the best tools and VLMs. We openly release all components of OLMOCR: our fine-tuned VLM model, training code and data, an efficient inference pipeline that supports vLLM and SGLang backends, and benchmark.<sup>1</sup>

## 1. Introduction

Access to clean, coherent text is essential for training modern language models (LMs) on trillions of tokens from billions of documents (Soldaini et al., 2024a; Penedo et al., 2024b; Li et al., 2024a); noisy or low-fidelity data can cause training instabilities and harm downstream performance (Penedo et al., 2023b; Li et al., 2024a; OLMo et al.,

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<sup>1</sup>Code is made anonymous for review at <https://anonymous.4open.science/r/olmocr-F583/>.

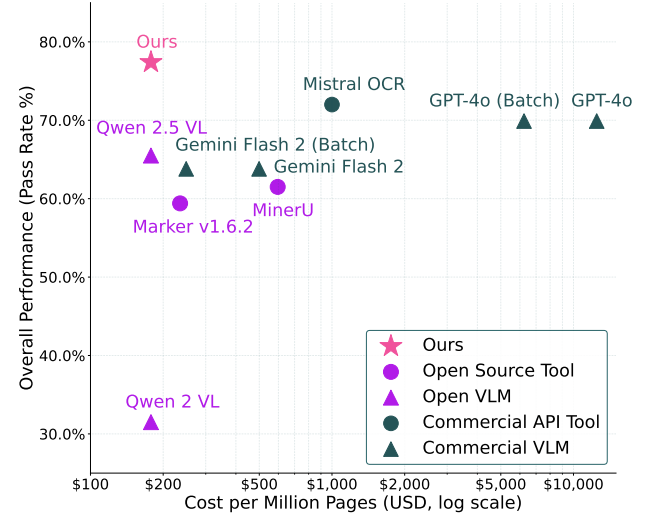


Figure 1. Performance-to-cost of OLMOCR vs other tools or models for PDF linearization and content extraction.

2024). Electronic documents, particularly PDFs, represent a significant repository of textual content, with trillions of documents stored in this format (PDF Association staff, 2015), which makes them critical for the development of language models. For example, Qwen 3 (Yang et al., 2025) described training on “trillions of tokens” from PDFs.

Faithful extraction and representation of digitized print documents has been studied since the 1950s, with commercial OCR tools emerging in the late 1970s (Mori et al., 1992). Tesseract’s 2006 release was a major milestone as a high-quality, open-source OCR toolkit (Smith, 2013). Modern PDF extraction tools are either **pipeline-based systems**—comprising multiple ML components (e.g., MinerU (Wang et al., 2024a), Marker (Paruchuri, 2025), Grobid (gro, 2008–2025), VILA (Shen et al., 2022), PaperMage (Lo et al., 2023a))—or **end-to-end models**, which parse documents in a single step (e.g., Nougat (Blecher et al., 2023), GOT Theory 2.0 (Wei et al., 2024)). While pipeline-based systems emphasize faithful extraction, end-to-end models have advanced **linearization**, addressing the challenge of preserving logical reading order in complex layouts. Recent proprietary VLMs have significantly improved end-to-end linearization and extraction (Bai et al.,

2025; Google, 2025), but at high cost—for example, processing a million pages with GPT-4o can exceed \$6,200 USD.<sup>2</sup>

We introduce **OLMOOCR**, a general-purpose context extraction and linearization toolkit to convert PDFs or images of documents into clean plain text suitable for language model development. Our contributions in this work are as follows:

- **Data.** We create `olmOCR-Mix`, a collection of 260,000 crawled PDF pages paired with their OCR output by GPT-4o, that we use to train our models. These documents represent a diverse set of publicly available PDFs, with a skew towards academic papers, public domain books, legal documents, brochures, and more.
- **Benchmark.** We develop `OLMOOCR-BENCH`, a comprehensive benchmark for evaluating document extraction tools. The benchmark covers 1,400 PDF pages with over 7,000 unit-test cases spanning diverse document types.
- **Model and Code.** We fine-tune Qwen2-VL-7B-Instruct (Wang et al., 2024b) on `olmOCR-Mix`, producing `olmOCR-7B`. We package our VLM in the `OLMOOCR` Python toolkit, written to scale efficiently from one to hundreds of GPUs using `SGLang` (Zheng et al., 2024) inference engine. `OLMOOCR` achieves state-of-the-art performance on our benchmark, even outperforming Qwen2.5-VL-7B while remaining more cost-effective than existing alternatives, including commercial APIs; `OLMOOCR` can produce high-quality plain text at less than \$176 per million PDF pages.

## 2. Creating and Training on `olmOCR-Mix`

### 2.1. Crawling PDFs

We randomly sample PDFs from an internal dataset of 240 million PDFs crawled from public internet sites, as well as PDFs of public domain books sourced from the Internet Archive. While the web crawled set is often born-digital documents, PDFs from the Internet Archive consist of image scans. We then perform a set of filters: Using the `Lingua` package (Emond, 2025), we identify and filter out non-English documents. Further, we remove any document that failed to be parsed by `pypdf`, contains spam keywords, is a fillable form, or whose text is too short. We then sampled (up to) three pages uniformly at random from each PDF. Our final set consists of 96,929 unique web-crawled PDF documents (totaling 240,940 pages) and 5,896 Internet Archive books (totaling 17,701 pages), for an overall total of 102,825 documents and 258,641 pages. Among the PDFs in the training set, 55.9% are academic documents, 11.2% are brochures, 10.2% are legal documents, 6.8% are books,

<sup>2</sup>Batch pricing at \$1.25 USD (input) and \$5.00 USD (output) per 1M tokens in Feb 2025. Details in Appendix A.

5.6% are tables, 4.7% are diagrams, 1.9% are slideshows, and 3.7% fall into other categories.

### 2.2. Generating Linearized Plain Text

We generated supervision data for PDF-to-plain-text conversion using GPT-4o, as human annotation is expensive and existing PDF extraction tools are unreliable, especially for document images.<sup>3</sup> To address the model’s occasional omissions and hallucinations—particularly on complex layouts—we augmented the PDF page images with extracted text blocks and layout information, using a noisy but useful PDF internal representation from `pypdf` (PyPDF, 2012–2025). We prompted GPT-4o with this combined visual and text input (called `DOCUMENT-ANCHORING`) to produce our final supervision targets. See Appendix Figure 2 for example and §B.1 for prompt.

### 2.3. Fine-Tuning `olmOCR-7B`

Starting from a Qwen2-VL-7B-Instruct checkpoint, we fine-tune `olmOCR-7B` on `olmOCR-Mix`. Training is implemented using Hugging Face’s `transformers` library (Wolf et al., 2020). We use an effective batch size of 4, learning rate of 1e-6, AdamW optimizer, and a cosine annealing schedule for 10,000 steps (roughly 1.2 epochs). We use single node with 8 x NVIDIA H100 (80GB) GPUs. A single training run took 16 node hours, with all training experiments totaling 365 node hours.

During fine-tuning, we slightly alter the `DOCUMENT-ANCHORING` prompt, removing some instructions and shrinking the image size so that PDF pages are rendered to a maximum dimension of 1024 pixels on the longest edge. The simplified text prompt is in Appendix §B.3. Loss was masked so only the final response tokens participated in the loss calculation.

## 3. Building `OLMOOCR-BENCH`

We develop `OLMOOCR-BENCH` to systematically evaluate PDF linearization and content extraction performance across diverse tools and models. `OLMOOCR-BENCH` operates by assessing a series of predefined pass-or-fail “unit-tests”—*Given an input whole PDF, does the plain text output satisfy a specific property or contain a specific element?* Each test is designed to be simple, unambiguous, and deterministically machine-verifiable. `OLMOOCR-BENCH` comprises

<sup>3</sup>In October 2024, we evaluated several leading VLMs for data generation. Gemini 1.5 was eliminated due to frequent `RECITATION` errors (though this was resolved by February 2025), GPT-4o mini produced excessive hallucinations, and Claude Sonnet 3.5 was cost-prohibitive. We selected `gpt-4o-2024-08-06` as it offered the optimal balance of accuracy, reliability, and cost-efficiency in batch mode.

1,402 distinct PDF documents derived from diverse source repositories, covered by 7,010 unique test cases.

### 3.1. Unit Test Categories

We designed five distinct test categories to assess different aspects of linearization and context extraction performance. **Text Presence** checks that a specific text segment appears in the plain text output, with options for fuzzy matching and positional constraints. In contrast, **Text Absence** ensures that a given segment does *not* appear—useful for filtering out headers, footers, or pagination. The **Natural Reading Order** category validates that two text segments appear in the correct order, while allowing for some flexibility and fuzzy matching. **Table Accuracy** evaluates whether a table cell and its neighbors in the output match expected values, supporting both Markdown and HTML formats. **Math Formula Accuracy** involves verifying that a math equation is present by comparing the visual layout of symbols to a rendered reference. Finally, the **Baseline** category confirms that the output includes reasonable alphanumeric text and avoids common issues like repeating patterns or unwanted character sets.

### 3.2. Sourcing Documents and Creating Tests

We define seven document types that posed challenges for OLMOCR and developed custom acquisition strategies for each. We filtered out documents containing PII and were not meant for public dissemination and performed URL-level deduplication against oLMOCR-Mix (Soldaini et al., 2024a). We created test cases using a mix of manual design and GPT-4o prompting; see Appendix §C for details and examples.

Our dataset construction drew from a range of sources and document types. The **arXiv Math (AR)** dataset consists of recent arXiv math papers with single TeX source files; for these, we identified and validated LaTeX expressions using our pipeline and manual review. The **Old Scans Math (OSM)** dataset was built by extracting pages with formulas from old public domain math textbooks, with each formula manually annotated as a test case. For the **Tables (TA)** dataset, we sampled PDFs containing tables, used Gemini-Flash-2.0 to generate cell relationship tests, and then manually reviewed the results. The **Old Scans (OS)** dataset comprises historical letters and typewritten documents with transcriptions from the Library of Congress<sup>4</sup> digital archives; we generated Natural Reading Order test cases for these and manually checked them for accuracy. In constructing the **Headers Footers (HF)** dataset, we sampled additional documents from our internal crawled PDFs, identified header and footer regions using DocLayout-YOLO (Zhao et al.,

<sup>4</sup><https://crowd.loc.gov>

2024), extracted their content with Gemini-Flash-2.0, and manually reviewed to ensure that such text is excluded from the linearized output. The **Multi Column (MC)** dataset includes multi-column PDFs sampled from our internal collection; for these, we used Claude-Sonnet-3.7 to extract the text order and manually verified that the text blocks were simple and coherent. Finally, the **Long Tiny Text (LTT)** dataset was created by crawling densely printed pages from the Internet Archive, generating test cases using Gemini-Flash-2.0, and manually verifying them.

### 3.3. Scoring

We run each of the PDF pages across each of our tools and methods to produce a markdown or plain text document. As all tests are Pass/Fail, we simply report percentage of tests passed, macro-averaged by document type.

## 4. Evaluating OLMOCR

### 4.1. OLMOCR-BENCH Results

Table 1 shows evaluation results of OLMOCR on OLMOCR-BENCH against a range of linearization tools and VLMs. We see that OLMOCR significantly outperforms both the best commercial dedicated OCR tool (Mistral) as well as both GPT-4o, its teacher model, and Qwen 2.5 VL, which is an update to Qwen 2 VL, which was the base model for oLMOCR-7B. We note that we developed OLMOCR-BENCH *after* training oLMOCR-7B to prevent unfairly iterating on the benchmark before comparing with other methods. Qualitatively, OLMOCR produces significantly cleaner plain text than specialized open-source tools (visualized in Appendix §E).

### 4.2. Downstream Evaluation

We demonstrate value of OLMOCR for curating language model pretraining data. Following (Blakeney et al., 2024; Grattafiori et al., 2024; OLMo et al., 2024), we experiment with continued pretraining of OLMo-2-1124-7B (OLMo et al., 2024) using content extracted from a fixed collection of PDFs but ablating the use of OLMOCR. For our baseline, we use tokens from peS2o (Soldaini & Lo, 2023), academic papers derived using Grobid (gro, 2008–2025) from the S2ORC (Lo et al., 2020) paper collection and further cleaned with heuristics for language modeling. Switching to using OLMOCR processing results in a **+1.3 percentage point average improvement** on widely-reported LM benchmark tasks.<sup>5</sup>

<sup>5</sup>Average of 55.2 (baseline) vs 53.9 (ours) over tasks including MMLU (Hendrycks et al., 2021), ARC<sub>C</sub> (Clark et al., 2018), DROP (Dua et al., 2019), HellaSwag (Zellers et al., 2019), NaturalQuestions (Kwiatkowski et al., 2019), WinoGrande (Sakaguchi et al., 2019).

Table 1. Evaluation results on OLMOCR-BENCH grouped by document types. Best unit test pass rate in each column is bold. 95% CI calculated by bootstrapping with 10k samples. Costs for API models using batch mode and for open VLM based on NVIDIA L40S.

Model	AR	OSM	TA	OS	HF	MC	LTT	Base	Overall	Cost per 1M pages
GOT OCR	52.7	52.0	0.2	22.1	93.6	42.0	29.9	94.0	48.3 ± 1.1	—
Marker v1.6.2	24.3	22.1	69.8	24.3	87.1	71.0	76.9	<b>99.5</b>	59.4 ± 1.1	\$235
MinerU v1.3.10	75.4	47.4	60.9	17.3	<b>96.6</b>	59.0	39.1	96.6	61.5 ± 1.1	\$596
Mistral OCR API	<b>77.2</b>	67.5	60.6	29.3	93.6	71.3	77.1	99.4	72.0 ± 1.1	\$1,000
GPT-4o	51.5	<b>75.5</b>	69.1	40.9	94.2	68.9	54.1	96.7	68.9 ± 1.1	\$6,240
Gemini Flash 2	32.1	56.3	61.4	27.8	48.0	58.7	<b>84.4</b>	94.0	57.8 ± 1.1	\$249
Qwen 2 VL	19.7	31.7	24.2	17.1	88.9	8.3	6.8	55.5	31.5 ± 0.9	\$176
Qwen 2.5 VL	63.1	65.7	67.3	38.6	73.6	68.3	49.1	98.3	65.5 ± 1.2	\$176
Ours	75.6	75.1	<b>70.2</b>	<b>44.5</b>	93.4	<b>79.4</b>	81.7	99.0	<b>77.4 ± 1.0</b>	\$176

## 5. Deploying OLMOCR

When considering real-world use, cost efficiency is just as important as performance.

**Inference Pipeline.** We deploy OLMOCR using SGLang (Zheng et al., 2024) for large-scale document processing. Documents are batched ( $\sim 500$  pages each) and processed on GPU workers, scaling easily from single to hundreds of nodes via a shared cloud bucket (e.g., S3). Workers queue and process all PDF pages in a batch together, maximizing GPU utilization and throughput.

As shown in Table 1, OLMOCR is significantly cheaper than both API and other local models—over  $32\times$  cheaper than GPT-4o and  $6\times$  cheaper than MinerU. To contextualize the value of OLMOCR, at 1,000 tokens per page, to process all of peS2o PDFs can already cost \$10.3M in H100 usage. In comparison, Mistral OCR is a commercial API tool specializing in this task, yet is over five times more expensive, making it even more prohibitive to use for language modeling. See Appendix §A for details on pricing and cost calculations.

**Improving Robustness.** Benchmark performance alone doesn’t guarantee real-world usability, so we employ several additional techniques to ensure reliability. For **Prompt Format**, we make sure that prompts match the training format, and if the length exceeds 8,192 tokens, we simply shorten the DOCUMENT-ANCHORING tokens until everything fits. With **Retries**, we rely on the model’s fine-tuning to keep outputs structured, so we don’t require strict schema enforcement—if a JSON parse fails, we just try again. When it comes to **Rotations**, any pages flagged for rotation are automatically corrected and reprocessed. For **Decoding**, we watch for output repetitions and, if they occur, retry with a higher generation temperature and different anchor tokens; if problems persist, we fall back on text extraction. Further optimizations to abort failed generations earlier are planned for future work.

## 6. Related Work

**PDF Linearization.** Many tools exist for linearizing PDFs to plain text, ranging from basic parsers and OCR to advanced models like LayoutLM (Xu et al., 2020), VILA (Lin et al., 2024), and production systems such as PaperMage (Lo et al., 2023b), Grobid (gro, 2008–2025), but comprehensive VLM-based libraries for this task remain scarce, a gap our work addresses while comparing to recent models like Mistral (Mistral, 2025) and Qwen VL (Bai et al., 2023).

**Benchmarking VLMs on Linearization.** Existing benchmarks for document linearization, like FUNSD (Guillaume Jaume, 2019), SROIE (Huang et al., 2019), and RVL-CDIP (Harley et al., 2015), are domain-limited and task-specific, whereas our approach introduces a broader, unit-test-style evaluation spanning diverse document types and extraction tasks (e.g., tables (Zhong et al., 2020), formulas (Zhong et al., 2021)) and supports flexible tokenization.

**Linearization for Language Modeling.** While there is significant research on data curation for language modeling (Soldaini et al., 2024b; Penedo et al., 2024a; Li et al., 2024b; Wettig et al., 2025; Liu et al., 2024), little attention has been given to how linearization quality affects downstream model training, especially for PDF content—a gap this work seeks to fill, unlike prior efforts focused on web content (e.g., DCLM (Li et al., 2024b), RefinedWeb (Penedo et al., 2023a), OpenWebMath (Paster et al., 2023)).

## 7. Conclusion

We present OLMOCR, an open-source toolkit that efficiently converts PDFs to clean text, matching commercial performance at lower cost. We release our model, training set (olmOCR-Mix), and a comprehensive benchmark (OLMOCR-BENCH) of 7,010 unit tests across 1,403 PDFs. We hope OLMOCR will unlock new training sources of high-quality PDF documents that are currently underrepresented amid heavy reliance on crawled web pages.



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## A. Cost Estimates of PDF Extraction Systems

To estimate prices (Table C.1.6), we use rates provided by RunPod<sup>6</sup> as of February 2025. It prices a single on-demand NVIDIA L40S GPU at \$0.79 USD per hour, and NVIDIA H100 80GB SXM at \$2.69 USD per hour. Using these rates, costs (in USD) were computed as follows:

- **GPT-4o**: We evaluated GPT-4o in February 2025. We tested 1288 pages, which resulted in 3,093,315 input tokens at 833,599 output tokens. Priced at \$2.50 per million input tokens and \$10.00 per million output tokens, it resulted in a total of \$16.07. Batch processing is priced at half of the cost, \$8.03.
- **Mistral OCR**: As of May 2025, Mistral prices their OCR service at \$1 per 1,000 pages, regardless of number of generated tokens.
- **MinerU**: We run the toolkit (version 1.3.10) on a single NVIDIA L40S GPU. It processed 1,288 pages in 58 minutes 22 seconds, costing \$0.767.
- **Marker**: We run marker locally on L40S, version 1.6.2. In our test on 1,166 pages, it took 20 minutes, 52 seconds to parse 1166; we consider this second run and estimate its cost to \$0.274. We note that this is much more cost-effective than using Marker APIs, which are priced at \$1.5 per 1000 standard pages, and \$3.0 per 1000 pages with layout/tables.
- **Gemini Flash 2.0**: As of February 2025, it is priced \$0.10 per 1 million input tokens, and \$0.40 per 1 million output tokens. In our testing over the same 1,288 pages used to evaluate GPT-4o, it cost in \$0.643.
- **OLMOOCR**: We tested OLMOOCR on both L40S and H100 GPUs. On L40s, it processed 1,288 test pages in 17 minutes, 10 seconds. The effective throughput of the model was 906 output tokens per second, plus a 12% retries rate. Overall, we estimate its costs at \$0.226. On H100, OLMOOCR generates 3,050 output tokens per second, resulting in a runtime of 5 minutes 7 seconds, for a cost of \$0.229.

## B. olmOCR-Mix and olmOCR-7B Prompts

### B.1. olmOCR-Mix construction prompt for GPT-4o

The prompt below was used to create the silver dataset, which we refer to as olmOCR-Mix throughout the paper. This dataset consists of structured outputs generated by GPT-4o, using images of PDF pages along with additional layout-aware textual features produced by our DOCUMENT-ANCHORING pipeline. We use this synthetic data to fine-tune our model.

In this prompt, the placeholder {base\_text} is replaced

<sup>6</sup><https://www.runpod.io>

with the structured layout-aware text extracted from the PDF using DOCUMENT-ANCHORING. The prompt instructs GPT-4o to output the natural reading-order text of the page, while respecting document semantics, suppressing hallucinations, and formatting content like equations and tables appropriately.

```
Below is the image of one page of a PDF
document, as well as some raw textual
content that was previously extracted
for it that includes position
information for each image and block of
text (The origin [0x0] of the
coordinates is in the lower left corner
of the image).
Just return the plain text representation
of this document as if you were reading
it naturally.
Turn equations into a LaTeX representation,
and tables into markdown format.
Remove the headers and footers, but
keep references and footnotes.
Read any natural handwriting.
This is likely one page out of several in
the document, so be sure to preserve
any sentences that come from the
previous page, or continue onto the
next page, exactly as they are.
If there is no text at all that you think
you should read, you can output null.
Do not hallucinate.
RAW_TEXT_START
{base_text}
RAW_TEXT_END
```

## B.2. JSON Schema used to prompt GPT-4o

```
"json_schema": {
  "name": "page_response",
  "schema": {
    "type": "object",
    "properties": {
      "primary_language": {
        "type": ["string",
          "null"],
        "description": "The
          primary
          language of the
          text using two
          -letter codes
          or null if
          there is no
          text at all
          that you think
          you should read
          .",
      },
      "is_rotation_valid": {
        "type": "boolean",
        "description": "Is
          this page
          oriented
          correctly for
```

```
reading? Answer
only
considering the
textual
content, do not
factor in the
rotation of any
charts, tables
, drawings, or
figures.",
},
"rotation_correction": {
  "type": "integer",
  "description": "
    Indicates the
    degree of
    clockwise
    rotation needed
    if the page is
    not oriented
    correctly.",
  "enum": [0, 90,
    180, 270],
  "default": 0,
},
"is_table": {
  "type": "boolean",
  "description": "
    Indicates if
    the majority of
    the page
    content is in
    tabular format
    .",
},
"is_diagram": {
  "type": "boolean",
  "description": "
    Indicates if
    the majority of
    the page
    content is a
    visual diagram
    .",
},
"natural_text": {
  "type": ["string",
    "null"],
  "description": "The
    natural text
    content
    extracted from
    the page.",
},
},
"additionalProperties":
  False,
"required": [
  "primary_language",
  "is_rotation_valid",
  "rotation_correction",
  "is_table",
  "is_diagram",
  "natural_text",
```

```

    ],
    },
    "strict": True,
  },

```

### B.3. olmoOCR-7B prompt

The prompt below is used to draw responses from our fine-tuned model during inference. As before, the placeholder {base\_text} is replaced with the output of the DOCUMENT-ANCHORING pipeline i.e., layout-aware textual features extracted from the PDF page.

```

Below is the image of one page of a
document, as well as some raw textual
content that was previously extracted
for it.
Just return the plain text representation
of this document as if you were reading
it naturally.
Do not hallucinate.
RAW_TEXT_START
{base_text}
RAW_TEXT_END

```

### B.4. olmoOCR-Mix Classification Prompt

The prompt and structured schema below was used to classify a sample of documents from olmoOCR-Mix.

```

This is an image of a document page, please
classify it into one of the following
categories that best overall summarizes
its nature: academic, legal, brochure,
slideshow, table, diagram, or other.
Also determine the primary language of
the document and your confidence in the
classification (0-1).

```

```

class DocumentCategory(str, Enum):
    ACADEMIC = "academic"
    LEGAL = "legal"
    BROCHURE = "brochure"
    SLIDESHOW = "slideshow"
    TABLE = "table"
    DIAGRAM = "diagram"
    OTHER = "other"

class DocumentClassification(BaseModel):
    category: DocumentCategory
    language: str
    confidence: float

```

### B.5. olmoOCR-Mix PII Prompt

We implemented comprehensive prompting for detecting personally identifiable information (PII) in the documents while cleaning the olmoOCR-Mix:

You are a document analyzer that identifies Personally Identifiable Information (PII) in documents.

Your task is to analyze the provided document image and determine:

- Whether the document is intended for public release or dissemination (e.g., research paper, public report, etc.)
- If the document contains any PII

For PII identification, follow these specific guidelines:

IDENTIFIERS FOR PII:

The following are considered identifiers that can make information PII:

- Names (full names, first names, last names, nicknames)
- Email addresses
- Phone numbers

PII THAT MUST CO-OCCUR WITH AN IDENTIFIER:

The following types of information should ONLY be marked as PII if they occur ALONGSIDE an identifier (commonly, a person's name):

- Addresses (street address, postal code, etc.)
- Biographical Information (date of birth, place of birth, gender, sexual orientation, race, ethnicity, citizenship /immigration status, religion)
- Location Information (geolocations, specific coordinates)
- Employment Information (job titles, workplace names, employment history)
- Education Information (school names, degrees, transcripts)
- Medical Information (health records, diagnoses, genetic or neural data)

PII THAT OCCURS EVEN WITHOUT AN IDENTIFIER:

The following should ALWAYS be marked as PII even if they do not occur alongside an identifier:

- Government IDs (Social Security Numbers, passport numbers, driver's license numbers, tax IDs)
- Financial Information (credit card numbers, bank account/routing numbers)
- Biometric Data (fingerprints, retina scans, facial recognition data, voice signatures)
- Login information (ONLY mark as PII when a username, password, and login location are present together)

If the document is a form, then only consider fields which are filled out with specific values as potential PII. If this page does not itself contain PII, but references documents (such as curriculum vitae, personal statements) that typically contain PII, then do not mark it as PII.

Only consider actual occurrences of the PII within the document shown.

6. The viewport is fixed at {png\_width // 2}x{png\_height // 2} pixels.

Enclose your HTML in a html code block.

## C. Further details of OLMOOCR-BENCH

### C.1. Prompting Strategies and Implementation Details

This section provides comprehensive documentation of the prompting techniques and design strategies to make OLMOOCR-BENCH. These prompting approaches were critical in generating test cases while utilizing LLMs and ensuring consistency across document categories.

#### C.1.1. MATHEMATICAL EXPRESSIONS

For generating mathematical expression test cases from old scans, we employed direct prompts focused on precision. This concise prompt architecture proved effective in extracting LaTeX representations minimizing hallucination. The explicit instruction to use standard LaTeX delimiters (\$\$) ensured consistent formatting across the OLMOOCR-BENCH.

Please extract the mathematical equations from the document without omission. Always output the mathematical equations as Latex escaped with \$\$. Do not hallucinate.

#### C.1.2. MULTI-COLUMN

For Multi-column documents, we utilized a two-stage prompting strategy. The initial analytical stage established structural context:

Analyze this document and provide a detailed assessment of its structure. Focus on the layout, headings, footers, and any complex formatting. Please be precise.

This preliminary analysis was incorporated into a subsequent HTML rendering prompt:

Render this document as clean, semantic HTML. Here is the analysis of the document structure:

{analysis\_text}

Requirements:

1. Use appropriate HTML tags for headings, paragraphs, and lists.
2. Use <header> and <footer> for top and bottom content.
3. For images, use a placeholder <div> with class 'image'.
4. Render math equations inline using \(( \)
5. Preserve any multi-column layout using CSS flexbox or grid.

This approach significantly helped in layout preservation in complex documents by providing explicit dimensional constraints and structural information.

#### C.1.3. PII DETECTION AND FILTERING

We use the same PII detection and filtering as for construction olmOCR-Mix; see Appendix §B.5.

#### C.1.4. CLEANING MATHEMATICAL EXPRESSIONS

Mathematical expression verification employed specialized prompting for validating equation presence and accuracy:

This is a mathematical expression verification task. I'm showing you a page from a PDF document containing mathematical expressions. Please verify if the following LaTeX expression:

{latex\_expression}

appears correctly in the document. Respond with a JSON object containing:

1. "status": "correct" or "incorrect"
2. "confidence": a value between 0 and 1 representing your confidence in the answer
3. "explanation": a brief explanation of why you believe the expression is correct or incorrect

Focus specifically on checking if this exact mathematical expression appears in the document.

#### C.1.5. CLEANING READING ORDER TESTS

For natural reading order test cases, we implemented below verification prompt to ensure appropriate text segment relationships:

Does the text in the 'before' field and the 'after' field appear in the same region of the page? Look at the PDF image and determine if these texts are located near each other or in completely different parts of the page. Different regions could be the captions for different images, or inside of different insets or tables. However, appearing the same column of text, or in the naturally flowing next column of text is close enough.

Before: {before\_text}



```
After: {after_text}

Respond with 'YES' if they appear in the
same region or column, and 'NO' if they
appear in
different regions. Then explain your
reasoning in 1-2 sentences.
```

#### C.1.6. HEADER AND FOOTER VERIFICATION

For validating header and footer text identification, we employed JSON-structured verification prompts:

```
This is a header and footer verification
task.
I'm showing you a page from a PDF document
containing headers and footers text.
Please verify if the headers or footers is
exactly matches the below text.
{header_footer_text}
Respond with a JSON object containing:
1. "status": "correct" or "incorrect"
2. "confidence": a value between 0 and 1
representing your confidence in the
answer
3. "explanation": a brief explanation of
why you believe the text is correct or
incorrect
Focus specifically on checking if this
exact header or footer expression
appears in the document.
```

Our prompting strategy deliberately requested different output formats for different content types (Markdown for general text, LaTeX for equations, HTML for tables) to optimize representation fidelity across diverse document elements. Low temperature settings (typically 0.1) was maintained across all the prompt executions to ensure reproducible outputs, particularly important for establishing consistent test cases.

### D. OLMOOCR-BENCH Sample Test Classes

Below are are few examples taken from OLMOOCR-BENCH

### E. Example OLMOOCR output

Below are some sample outputs on particularly challenging data. OLMOOCR, MinerU, GOT-OCR 2.0 and Marker run with default settings.

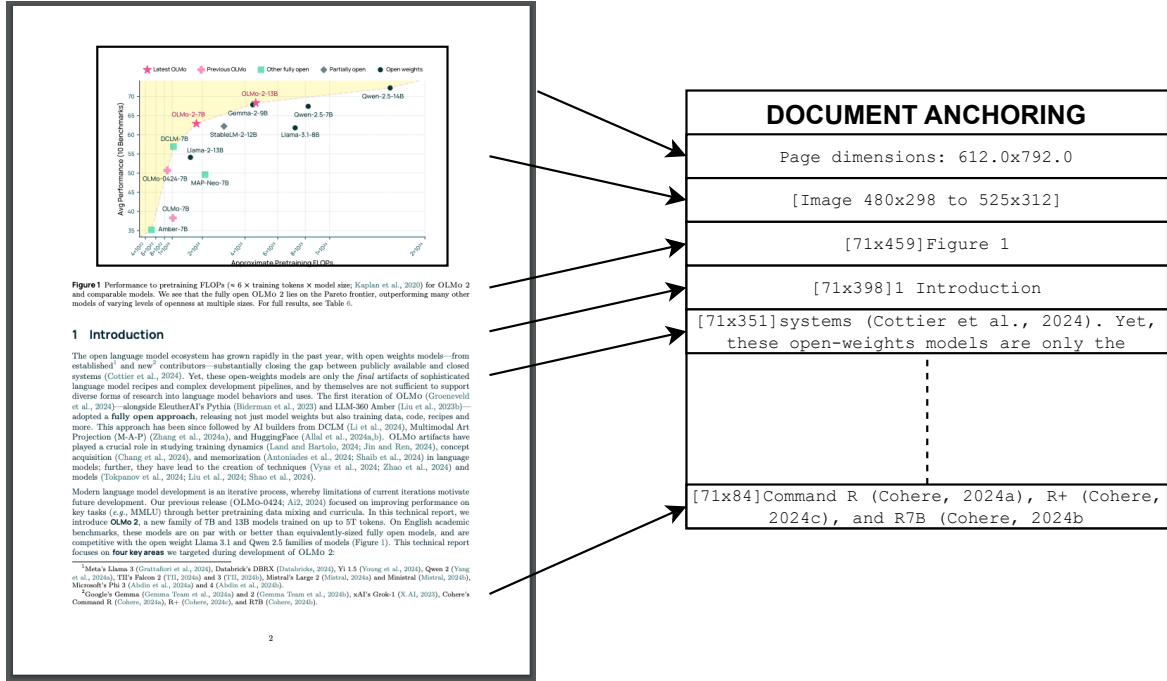


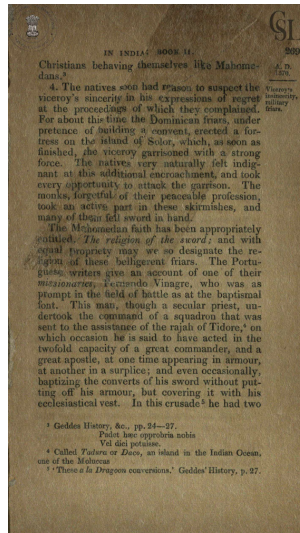
Figure 2. Example of how DOCUMENT-ANCHORING works for a typical page. Relevant image locations and text blocks get extracted, concatenated, and inserted into the model prompt. When prompting a VLM for a plain text version of the document, the anchored text is used in conjunction with the rasterized image of a page.

Table 2. Inference cost comparison against other OCR methods. NVIDIA L40S estimated at \$0.79 per hour, H100 80GB estimated at \$2.69 per hour. We measured a 12% retry rate for OLMOOCR. Full cost breakdown in Appendix A.

Model	Hardware	Tokens/sec	Pages/USD	Cost per million pages
GPT-4o	API	-	80	\$12,480
	Batch	-	160	\$6,240
Mistral OCR	API	-	1,000	\$1,000
MinerU	L40S	238	1,678	\$596
Gemini Flash 2	API	-	2,004	\$499
	Batch	-	4,008	\$249
Marker v1.6.2	L40S	690	4,244	\$235
OLMOOCR	L40S	906	<b>5,697</b>	<b>\$176</b>
	H100	3,050	<b>5,632</b>	<b>\$178</b>

Table 3. Counts of PDF document types and unit test types in OLMOOCR-BENCH.

	Presence	Absence	Read Order	Table	Formula	Total Tests
arXiv Math (AM)	-	-	-	-	2,927	2,927
Old Scans Math (OSM)	-	-	-	-	458	458
Tables (TA)	-	-	-	1,020	-	1,020
Old Scans (OS)	279	70	177	-	-	526
Headers Footers (HF)	-	753	-	-	-	753
Multi Column (MC)	-	-	884	-	-	884
Long Tiny Text (LTT)	442	-	-	-	-	442
Total PDFs	721	823	1,061	1,020	3,385	7,010



OLMOOCR

MinerU

GOT-OCR 2.0

Marker

Christians behaving themselves like Mahomedans.

4. The natives soon had reason to suspect the viceroy's sincerity in his expressions of regret at the proceedings of which they complained. For about this time the Dominican friars, under pretence of building a convent, erected a fortress on the island of Solor, which, as soon as finished, the viceroy garrisoned with a strong force. The natives very naturally felt indignant at this additional encroachment, and took every opportunity to attack the garrison. The monks, forgetful of their peaceable profession, took an active part in these skirmishes, and many of them fell sword in hand.

The Mahomedan faith has been appropriately entitled, The religion of the sword; and with equal propriety may we so designate the religion of these belligerent friars. The Portuguese writers give an account of one of their missionaries, Fernando Vinagre, who was as prompt in the field of battle as at the baptismal font. This man, though a secular priest, undertook the command of a squadron that was sent to the assistance of the rajah of Tidore, on which occasion he is said to have acted in the twofold capacity of a great commander, and a great apostle, at one time appearing in armour, at another in a surplice; and even occasionally, baptizing the converts of his sword without putting off his armour, but covering it with his ecclesiastical vest. In this crusade he had two

ININDIASY BOOKU Christians behaving themselves like Mahomedans.3

4. The natives soon had reason to suspect the viceroy's sincerity in his expressions of regret at the proceedings of which they complained. For about this time the Dominican friars, under pretence of building a convent, erected a fortress on the island of Solor, which, as soon as finished, the viceroy garrisoned with a strong force. The natives very naturally felt indignant at this additional encroachment, and took every opportunity to attack the garrison. The monks, forgetful of their peaceable profession took an active part in these skirmishes, and many of them fell sword in hand.

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IN INDIA: BOOK U 269 Christians behaving themselves like Mahomedans. 4. The natives soon had reason to suspect the Viceroy's sincerity in his expressions of regret at the proceedings of which they complained. For about this time the Dominican friars, under pretence of building a convent, erected a fortress on the island of Solor, which, as soon as finished, the viceroy garrisoned with a strong force. The natives very naturally felt indignant at this additional encroachment, and took every opportunity to attack the garrison. The monks, forgetful of their peaceable profession, took an active part in these skirmishes, and many of them fell sword in hand. The Mahomedan faith has been appropriately entitled. The religion of the sword; and with equal propriety may we so designate the religion of these belligerent friars. The Portuguese writers give an account of one of their missionaries, Fernando Vinagre, who was as prompt in the field of battle as at the baptismal font. This man, though a secular priest, undertook the command of a squadron that was sent to the assistance of the rajah of Tidore, on which occasion he is said to have acted in the twofold capacity of a great commander, and a great apostle, at one time appearing in armour, at another in a surplice; and even occasionally, baptizing the converts of his sword without putting off his armour, but covering it with his ecclesiastical vest. In this crusade he had two 3 Geddes History, & c., pp. 24-27. Pudet hæc opprobria nobis Vel die ipo tui sse. Called Tadoru or Daco, an island in the Indian Ocean, one of the Moluccas These a la Dragon conversions. Geddes History, p. 27.

## \*\*IN INDIA \*\*\* BOOK TI. S69 Christians behaving themselves like Mahomedans. 4. The natives soon had reason to suspect the viceroy's sincerity in his expressions of regret at the proceedings of which they complained. For about this time the Dominican friars, under pretence of building a convent, erected a fortress on the island of Solor, which, as soon as finished, the viceroy garrisoned with a strong force. The natives very naturally felt indignant at this additional encroachment, and took every opportunity to attack the garrison. The monks, forgetful of their peaceable profession, took an active part in these skirmishes, and many of them fell sword in hand. The Mahomedan faith has been appropriately entitled. The religion of the sword; and with equal propriety may we so designate the religion of these belligerent friars. The Portuguese writers give an account of one of their missionaries, Fernando Vinagre, who was as prompt in the field of battle as at the baptismal font. This man, though a secular priest, undertook the command of a squadron that was sent to the assistance of the rajah of Tidore, on which occasion he is said to have acted in the twofold capacity of a great commander, and a great apostle, at one time appearing in armour, at another in a surplice; and even occasionally, baptizing the converts of his sword without putting off his armour, but covering it with his ecclesiastical vest. In this crusade he had two 3 Geddes History, & c., pp. 24-27. Pudet hæc opprobria nobis Vel dici potuisse. 4 Called Tadoru or Daco, an island in the Indian Ocean, one of the Moluccas These a la Dragon conversions. Geddes History, p. 27.



## 626 ANSWERS AND HINTS

denoting differentiation with respect to  $y$ . Using the relations  $x^2 = 1$ ,  $\dot{x}x = 0$ , we obtain the equations  $(y - x)x = 0$ ,  $(y - x)x = 1$ ,  $(y - x)x = 0$ . Hence we have  $y - x = \frac{[xx]}{[xx]x}$ .

5. Cf. Ex. 3 and also Ex. 5, p. 19

7. From the definitions of  $\xi_1, \xi_2, \xi_3$  we have  $\xi_1 = x$ ,  $\dot{x}^2 = 1$ ,  $\xi_2 = x/k$ ,  $\xi_3 = [\xi_1 \xi_2]$ ,  $\pm \sqrt{\xi_3^2} = 1/\tau$ . Obviously  $\xi_1 = k\xi_2$ . To determine  $\xi_2, \xi_3$ , we calculate their components with respect to a rectangular coordinate system  $O\xi_1, O\xi_2, O\xi_3$ . From the relations

$$\xi_2^2 = 1, \xi_3^2 = 1, \xi_1 \xi_2 = \xi_2 \xi_3 = \xi_3 \xi_1 = 0$$

we obtain by differentiation

$$\xi_3 \dot{\xi}_1 = -\xi_1 \dot{\xi}_3 = 0, \xi_3 \dot{\xi}_2 = 0;$$

hence  $\xi_3$  is perpendicular both to  $\xi_1$  and to  $\xi_2$ , and therefore

$$\xi_3 = \pm \sqrt{(\xi_1^2)} \xi_2 = \pm \xi_2/\tau.$$

We define the sign of  $\tau$  so as to give  $\xi_3 = -\xi_2/\tau$ . This implies that  $\tau$  is positive or negative according as the screw defined by the motion of the osculating plane in the direction of increasing  $s$  is right-handed or left-handed. To prove the second formula, note that

$$\xi_2 \dot{\xi}_1 = -\xi_1 \dot{\xi}_2 = -k, \xi_2 \dot{\xi}_2 = 0, \xi_2 \dot{\xi}_3 = -\xi_3 \dot{\xi}_2 = 1/\tau.$$

8. Use Ex. 6 and Ex. 3: (a)  $k\xi_2 - k^2\xi_1 + \frac{k}{\tau}\xi_3$ , (b)  $\frac{k}{k^2\tau}\xi_3 + \frac{\xi_2}{\tau}$

9.  $1/|\tau| = \sqrt{\xi_3^2} = 0$ , hence  $\xi_3$  is a constant vector  $\eta$ , say;  $\tau\eta = \xi_1\eta = \xi_2\eta = 0$ , so that  $x\eta = \text{const.}$ , where  $\eta$  is a fixed vector. That is, the curve lies in a fixed plane.

10. (b) If the curve is given by  $x = f(t)$ ,  $y = g(t)$ ,  $z = h(t)$ , the surface has the parametric equations

$$\begin{aligned} x &= f(t) + sf'(t) \\ y &= g(t) + sg'(t) \\ z &= h(t) + sh'(t), \end{aligned}$$

Figure 3. Sample visualization from old\_scans\_math. The OCR output for the highlighted equation should be:  $1/|\tau| = \sqrt{\xi_3^2} = 0$

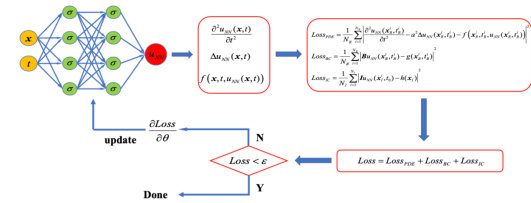


Figure 2: FPINN framework to solve wave propagation

## 3. Normalized Fourier induced PINN to solve the wave equation

## 3.1. The analysis of general PINN and FPINN method to the wave equation in two different scale range

Although various PINN models have been successfully applied to the study of ordinary and partial differential equations, particularly in the case of the wave equation, our investigation shows that their performance deteriorates in large scale domain and long time range, potentially leading to non-convergence.

For example, let us consider two scenarios for two-dimensional wave propagation equation with Dirichlet boundary in  $\Omega_1 = [0, 2\pi] \times [0, 2\pi]$ ,  $t \in (0, 2)$ .  $\Omega_2 = [0, 10\pi] \times [0, 10\pi]$ ,  $t \in (0, 10)$ , respectively. The governed equation is

$$\frac{\partial^2 u}{\partial t^2} = \frac{1}{2} \left( \frac{\partial^2 u}{\partial x_1^2} + \frac{\partial^2 u}{\partial x_2^2} \right) + 12t^2 \quad (3.1)$$

An analytical solution is given by

$$u(x_1, x_2, t) = t^4 + \sin(x_1) \cdot \sin(x_2) \cdot \sin(t).$$

Since the boundary and initial constraint functions can be directly derived from the exact solution, we will not explicitly state them here.

In this experiment, the solvers for PINN and FPINN are configured as a DNN and a FFM-based DNN with  $N$  subnetworks, respectively, and the scale factors are set as  $\{1, 2, 3, 4, 5, 6, 7, 8, 9, 10\}$ , and each subnetwork is configured with sizes of  $(20, 15, 15, 10)$ . The first hidden layer of all subnetworks employs Fourier feature mapping as the activation function (see Eq. (2.3)), while the activation functions for the other layers (except for the output layer) are selected as  $\text{GELU}(x) = x \cdot \frac{1}{2} [1 + \text{erf}(\frac{x}{\sqrt{2}})]$ , where  $\text{erf}(x)$  is Gaussian error function, and the output layers of all subnetworks are linear. We train the previously mentioned PINN and FPINN models for 30,000 epochs, performing testing every 1,000 epochs during the training process.

Figure 4. Sample visualization of a math equation from arXiv\_math. The OCR output for the highlighted equation should be:  $u(x_{\{1\}}, x_{\{2\}}, t) = t^4 + \sin(x_{\{1\}}) \cdot \sin(x_{\{2\}}) \cdot \sin(t)$

DE GRUYTER

Åberg and Mikkelson: Two TSH results from the same patient — 3

**Table 1:** Classification of two simulated s-TSH values from 100,000 individuals according to the bivariate distribution and the combination of RCVs and univariate reference limits. Classified as normal according to the bivariate distribution were the pairs of measurement within the central 95 % of that distribution. Classified as normal according to the combination of RCVs and univariate reference limits were those pairs of measurements where the difference between them was within RCVs and both measurements were within the univariate reference range.

Combination of non-parametric RCVs and reference limits	Bivariate distribution		Total
	Normal	Abnormal	
Normal	87,608	992	88,600
Abnormal	7,392	4,008	11,400
Total	95,000	5,000	100,000

and 0.960 (95 % CI 0.957 to 0.962) for those with x1 above the median.

The graphical study of the s-sodium data is presented in a supplementary figure. The sensitivity of the combination of univariate reference limits and RCVs for identifying pairs of x1 and x2 lying outside the central 95 % of the bivariate distribution of s-sodium was 100 %. The specificity for identifying pairs of x1 and x2 lying inside the central 95 % of the bivariate distribution was 92.5 %.

## Discussion

If the physician does not know the patient's setpoint value of s-TSH and wants to judge the clinical condition from s-TSH in two samples taken a time apart, we believe that the physician basically wants to assess whether the patient is healthy and stable. Then the two s-TSH values could be compared against the bivariate distribution in Figure 1, which represents a stable, euthyroid population. As clearly shown in Figure 1, the lines of the 2.5 and 97.5 percentile univariate reference limits in combination with the 2.5 and 97.5 percentile RCVs do not accurately delineate the central 95 % of the points of the bivariate distribution of x1 and x2. The space between the RCV lines contains 95 % of the points, as do the space between each set of reference limits, but the space between the RCVs and the reference limits is not congruent with the ellipse marking the central 95 % of the bivariate distribution. The RCV lines are approximately tangent to the ellipse marking the central 50 % of the distribution and cut through the other ellipses. Compared to the central 95 % of the bivariate distribution, the combination of univariate reference limits and RCVs had a fair specificity of 92.2 % but a lower sensitivity of 80.2 %. Without the assistance of univariate reference limits, the RCVs showed a particularly low sensitivity. Obviously, RCVs are not designed to detect healthiness, as the

area between the limits of RCVs includes analyte concentrations from zero to infinity (Figure 1). These considerations are not limited to s-TSH; probability density contour plots for bivariate distributions are not straight lines for any analyte, as indicated in the Supplementary Figure. In the example of s-sodium, the diagnostic accuracy of the univariate reference limits and RCVs was considerably better than for s-TSH. Obviously, how well the combination of univariate reference limits and RCVs delineate the corresponding bivariate distribution must be studied for each analyte.

Looking at the ellipses marking the various central proportions of the bivariate distribution and the line of equality (Figure 1), it is obvious that regression towards the mean does occur in this scenario. If the measured value in the first specimen (x1) is relatively low, the measured value in the second specimen (x2) is most likely to be higher, and vice versa. The median values of the difference x2 - x1 and the ratio x2/x1 for pairs with x1 below and above the median value of x1 showed the same phenomenon, as expected, because a difference in percent is equivalent to a ratio. We prefer ratios in this setting.

Thus, the idea of RCVs as a constant fraction of the first measurement is flawed, a finding in accordance with a previous study [7]. We estimated the RCVs both parametrically and non-parametrically, to see whether the two methods gave different results. They did not; the two methods of estimation gave almost identical RCV lines. They were symmetrical about the equality line, and asymmetrical in the y direction. We simulated the s-TSH-values assuming a Gaussian distribution around the setpoints; still, the non-parametrically derived RCVs based on the simulated values were asymmetrical in the y direction.

We believe our data set was theoretically sound. Data were derived from a Gaussian distribution truncated at ±3 standard deviation, and transformed to lognormally distributed data as coming from an euthyroid (healthy) population. Each data pair was generated from the same, individual setpoint value, so the data represented a stable population. All data pairs were generated with the same CV, of 17.9 % [4], thus the variance was homogeneous. The value of 3.4 % for CV<sub>Δ</sub> is the total CV<sub>Δ</sub> in our laboratory, estimated from quality control values over several months. Truncation at ±3 standard deviation when generating population setpoint and individual values were done because those distributions are not really Gaussian (they do not include values from minus to plus infinity) and often values outside ±3 standard deviation are regarded as outliers.

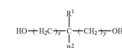
Note that this work deals with how the physician might interpret two s-TSH values from the same patient when the patient's setpoint value is unknown. It has no relevance if the physician needs to judge a time series of three or more measured values of the same analyte. Neither does it go

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(a) an unsaturated diol of the formula



in which R<sup>1</sup> is a substituted or unsubstituted alkyl group, substituted or unsubstituted aryl group, or substituted or unsubstituted alkyl-aryl group, which may

be a chain extender having at least two reaction sites with isocyanate and having a molecular weight of less than about 450; (c) a long chain polyol having a molecular weight of between about 500 and about 4,000; and (d) a sufficient amount of free radical initiator so as to be capable of generating free radicals that induce crosslinking structures in the hard segments by free radical initiation, wherein the mixture has a stoichiometric excess of isocyanate moieties of at least about 1 mol percent; wherein forming the outer cover layer further comprises applying the composition over the golf ball precursor and then moisture curing the composition; and wherein the outer cover layer has a flexural modulus between 400 psi and 900 psi.

2. The method of making the golf ball according to claim 1, wherein the organic isocyanate moieties to the hydroxyl moieties are in a molar ratio of from about 1.06:1.00 to about 1.18:1.00.

3. The method of making the golf ball according to claim 2, wherein the molar ratio is from about 1.10:1.00 to about 1.15:1.00.

4. The method of making the golf ball according to claim 1, wherein the free radical initiator is present in the mixture in a weight ratio of free radical initiator to unsaturated diols of from about 0.1:100 to about 100:100.

5. The method of making the golf ball according to claim 4, wherein a weight ratio of the crosslinked thermoplastic polyurethane elastomer to the unsaturated diols is about 100:10.

6. The method of making the golf ball according to claim 1, wherein the unsaturated diol is trimethylolpropane monoallyl ether.

7. The method of making the golf ball according to claim 1, wherein the free radical initiator generates free radicals through at least one of thermal cleavage and UV radiation cleavage.

8. The method of making the golf ball according to claim 1, wherein the free radical initiator is selected from the group consisting of peroxides.

9. The method of making the golf ball according to claim 1, wherein the step of forming a golf ball precursor further comprises the steps of: forming an inner core layer comprising a highly neutralized acid polymer; forming an outer core layer substantially surrounding the inner core layer; and

inches behind the point in the downsloping where the club was vertical. The height of the tee and the toe-heel position of the club relative to the tee were adjusted in order that the center of the impact mark was about ¼ of an inch above the sole and was centered to heel across the face. Three samples of each ball were tested. Each ball was hit three times.

Other methods may also be used to determine the scuff resistance, such as the methods described in the commonly assigned pending application titled "Golf Ball Wear Indicator," U.S. application Ser. No. 12/691,282, filed Jan. 21, 2010, in the name of Brad Titmuck.

After the above described scuff resistance testing, each golf ball cover was visually observed and rated according to the following scale: a golf ball cover was rated "1" when little or no damage was visible, no groove markings or dents; a golf ball cover was rated "2" when small cuts and/or ripples in the cover were apparent; a golf ball cover was rated "3" when moderate amounts of cover material were lifted from the ball's surface, but the cover material was still attached to the ball, and finally a golf ball cover was rated "4" when cover material was removed or barely attached to the golf ball.

Shore D hardness values of the core and cover layer were measured on the spherical surface of the layer to be measured by using a Shore D hardness tester.

As shown in Table 5, golf ball examples 1 and 2 made from compositions including a cross-linked thermoplastic polyurethane elastomer having cross-links located in the hard segments, where the cross-links are the reaction product of unsaturated bonds located in the hard segments as catalyzed by a free radical initiator and a proper ratio of the organic isocyanate to the long chain polyol, provides superior scuff resistance.

Additional golf balls are made in accordance with the method and comprising the compositions of Examples 1 and 2, with the exception that the index is 1.20 in one golf ball, 1.30 in another, and 1.40 in a third. The golf balls then are subjected to the scuffing test, and provide a scuff resistance rating of 1.5, 1.5, and 1.

While various embodiments of the invention have been described, the description is intended to be exemplary, rather than limiting and it will be apparent to those of ordinary skill in the art that many more embodiments and implementations are possible that are within the scope of the invention. Accordingly, the invention is not to be restricted except in light of the attached claims and their equivalents. Also, various modifications and changes may be made within the scope of the attached claims. For example, different golf ball precursors, perhaps those having a different number of layers or a different core composition, also fall within the scope of the claims.

We claim:

1. A method of making a golf ball, comprising the steps of: forming a golf ball precursor, the precursor having at least one golf ball layer but not an outer cover layer and forming an outer cover layer substantially surrounding the golf ball precursor.

wherein the outer cover layer comprises a composition of an over-indexed, crosslinked thermoplastic polyurethane elastomer including crosslinks formed from allyl groups and the thermoplastic polyurethane elastomer is a reaction product formed from reacting a mixture of a diisocyanate and:

Figure 5. Sample visualization of headers\_footers. We want the OCR to skip the document headers and page number.

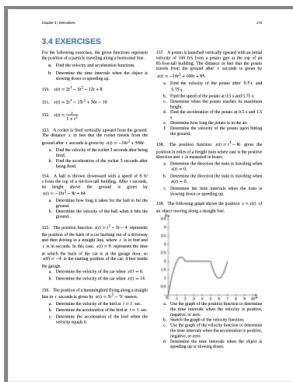
**Table 14:** Logistic regression analysis of the association of individual somatic depressive symptoms (dichotomous) with serum pyridoxal 5'-phosphate in women (n=1,489)

	Somatic Depression Symptoms							
	Sleeping problems		Fatigue		Abnormal appetite		Psychomotor abnormalities	
	OR (95% CI)	p-value	OR (95% CI)	p-value	OR (95% CI)	p-value	OR (95% CI)	p-value
<b>Unadjusted Model</b>								
PLP <20nmol/L	2.82 (1.68, 4.72)	<0.001	1.96 (1.33, 2.90)	0.001	2.94 (1.68, 5.13)	<0.001	2.63 (1.04, 6.65)	0.04
PLP 20-29.9	1.45 (0.89, 2.37)	0.13	1.24 (0.73, 2.11)	0.42	1.53 (0.86, 2.72)	0.14	0.71 (0.27, 1.83)	0.46
PLP ≥30 nmol/L	ref		ref		ref		ref	
<b>Adjusted Model</b>								
PLP <20nmol/L	1.60 (0.52, 4.90)	0.40	0.96 (0.58, 1.58)	0.85	0.79 (0.25, 2.57)	0.69	2.02 (0.45, 9.09)	0.35
PLP 20-29.9	1.10 (0.63, 1.94)	0.73	0.68 (0.31, 1.48)	0.32	1.11 (0.60, 2.07)	0.73	0.21 (0.03, 1.34)	0.10
PLP ≥30 nmol/L	ref		ref		ref		ref	

Adjusted model includes age, ethnicity, smoking, oral contraceptive use, sleep duration, physical activity, body mass index, CRP and mutually adjusted for the sum of the remaining depression items.

Figure 6. Sample visualization of table\_tests. We want the OCR to predict that cell 1.96 is to the left of cell 0.001.

Figure 7. Sample visualization of reading\_order. The reading order should start with the left column before moving to the right column.



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GOT-OCR 2.0

Marker

### 3.4 EXERCISES

For the following exercises, the given functions represent the position of a particle traveling along a horizontal line.

- Find the velocity and acceleration functions.
- Determine the time intervals when the object is slowing down or speeding up.

150.  $s(t) = 2t^3 - 3t^2 - 12t + 8$

151.  $s(t) = 2t^3 - 15t^2 + 36t - 10$

152.  $s(t) = \frac{t}{1+t^2}$

153. A rocket is fired vertically upward from the ground. The distance  $s$  in feet that the rocket travels from the ground after  $t$  seconds is given by  $s(t) = -16t^2 + 560t$ .

- Find the velocity of the rocket 3 seconds after being fired.
- Find the acceleration of the rocket 3 seconds after being fired.

154. A ball is thrown downward with a speed of 8 ft/s from the top of a 64-foot-tall building. After  $t$  seconds, its height above the ground is given by  $s(t) = -16t^2 - 8t + 64$ .

- Determine how long it takes for the ball to hit the ground.
- Determine the velocity of the ball when it hits the ground.

155. The position function  $s(t) = t^2 - 3t - 4$  represents the position of the back of a car backing out of a driveway and then driving in a straight line, where  $s$  is in feet and  $t$  is in seconds. In this case,  $s(t) = 0$  represents the time at which the back of the car is at the garage door, so  $s(0) = -4$  is the starting position of the car, 4 feet inside the garage.

- Determine the velocity of the car when  $s(t) = 0$ .
- Determine the velocity of the car when  $s(t) = 14$ .

156. The position of a hummingbird flying along a straight line in  $t$  seconds is given by  $s(t) = 3t^3 - 7t$  meters.

- Determine the velocity of the bird at  $t = 1$  sec.
- Determine the acceleration of the bird at  $t = 1$  sec.
- Determine the acceleration of the bird when the velocity equals 0.

157. A potato is launched vertically upward with an initial velocity of 100 ft/s from a potato gun at the top of an 85-foot-tall building. The distance in feet that the potato travels from the ground after  $t$  seconds is given by  $s(t) = -16t^2 + 100t + 85$ .

### # 3.4 EXERCISES

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Chapter 3 | Derivatives 273 3.4 EXERCISES For the following exercises, the given functions represent the position of a particle traveling along a horizontal line.

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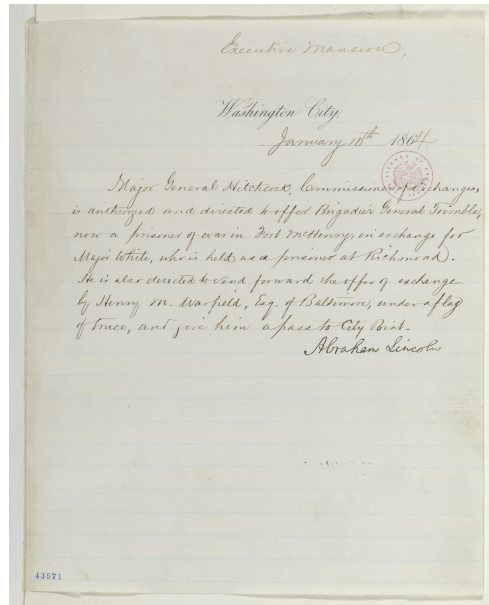
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- Determine the acceleration of the bird at  $t = 1$  sec.
- Determine the acceleration of the bird when the velocity equals 0.

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Executive Mansion, Washington City, January 15th, 1864 Major General Hitch- cock, Commissioner of Exchanges, is autho- rized and directed to offer Brigadier General Trimble, now a prisoner of war in Fort McHenry, in exchange for Major White, who is held as a prisoner at Richmond. He is also directed to send forward the offer of exchange by Henry M. Warfield, Esq. of Baltimore, under a flag of truce, and give him a pass to City Point. Abraham Lincoln	No text produced.	43571 Bachington City January 10th 1864. Major General Archi- tect, Commissioner of aivachangera is autho- rized and directed by ffeed Bngader General Trelmble, new a firemen of war in Fert nchery in exchange for Mayor White, who held a a firemen at Hillmannd. He is aker conducted by end forward the offer of exchange by Henry in. Warfield, Lag. of Balthmore, under a flag of three, and five him afaies to City Bink. Abraham Lincoln	necuhve Mansion Vast- ington amany layor Sen- eral Hitchcocks Com- missioner of Cachanges, is anthonged and di- rected to offer Bingadier General Trin prisoner of war in Fort Incti- enny, in exchange now w Major White, who is held as a preises at Richmond Ite is also di- rected to vand forwards the offer of exchange by Stenny in. Warfield, Eag. of Baltimore, un- der aflag 11 mice, and give him a pass to tity Point. Abrakan Sinco- lus