We'll get you there.

CPAs | CONSULTANTS | WEALTH ADVISORS

Data Science @ CLA

"A meta scene involving students and their professor"

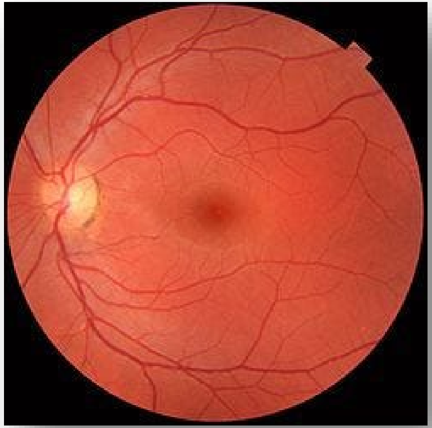
What is CLA?

Jen Leary, CEO

A Motivating Example

A Motivating Example

Can anyone spot the difference between these two photos?



A Motivating Example

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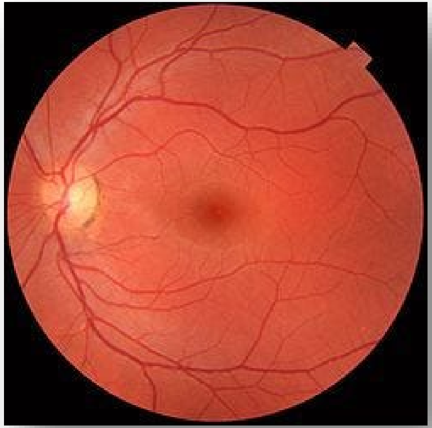

Healthy

Macular edema

A Motivating Example

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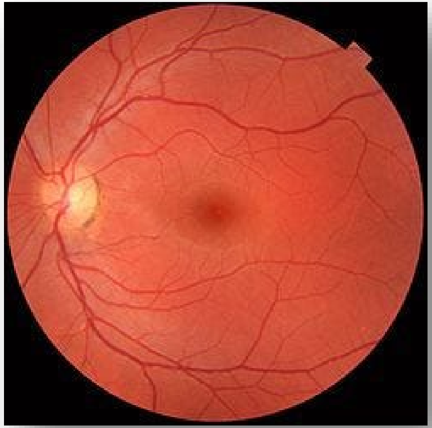

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Macular edema

- **Hundreds of Ophthalmologists**: ~50% (no better than a coin toss)

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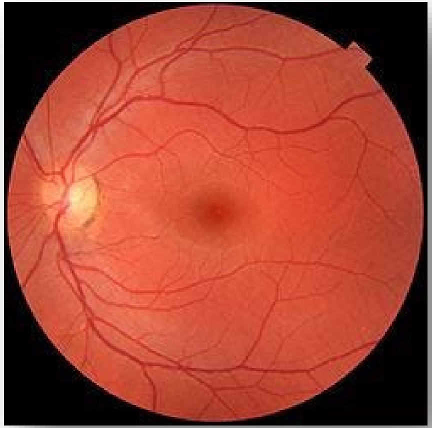


Healthy

Macular edema

- **Hundreds of Ophthalmologists**: ~50% (no better than a coin toss)
- **AI**: Near 100% accuracy

Images: Häggström, M. (2014). Medical gallery of Mikael Häggström 2014, WikiJournal of Medicine, 1(2).
Study: DeepMind & Moorfields Eye Hospital, *Nature Medicine* (2018)

What can we do with it?

Which transactions are likely to be fraudulent?

Which stores or locations are underperforming, and why?

What products should we recommend to this customer based on their past behavior?

Which employees are at risk of leaving the company?

Which customers are most likely to cancel their subscription next month?

Can we predict if a loan applicant will default?

Are there patterns in our expense data that suggest overspending or inefficiencies?

How should we allocate our marketing budget to maximize ROI?

Where are we losing the most time or money in our supply chain?

Which marketing campaigns lead to the highest customer lifetime value?

Can we predict which equipment is likely to fail before it happens?

How can we predict product demand next quarter to avoid overstocking?

Can we segment our customers into meaningful groups for targeted outreach?

How can we forecast hiring needs for the next 12 months?

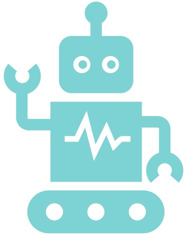
What's the optimal price point for our new product?

Types of Problems

Insight

Gaining a deeper understanding of data to inform better decisions

<u>**Example**</u>: Analyzing soil, weather, and crop health data to **optimize potato yields** and **minimize disease**.



Automation

Replacing manual, repetitive tasks with data-driven systems

<u>**Example**</u>: **Automating** manual data entry by **extracting** and **categorizing** data.

Insights

Insights | Potato Farm Yield Optimization

Imagine you own a potato farm… easy, right?

Till the soil → Plant the seeds → Harvest → Sell

Insights | Potato Farm Yield Optimization

Temperature (by hour)

Insights | Potato Farm Yield Optimization

Temperature (by hour)

Humidity

Insights | Potato Farm Yield Optimization

- Temperature (by hour)
- Humidity
- Precipitation

Insights | Potato Farm Yield Optimization

- Temperature (by hour)
- Humidity
- Precipitation
- Wind Velocity & Direction

Insights | Potato Farm Yield Optimization

- Temperature (by hour)
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- Daily NO_3 Applied

Insights | Potato Farm Yield Optimization

- Temperature (by hour)
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Insights | Potato Farm Yield Optimization

- Temperature (by hour)
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- Daily NO_3 Applied
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- Daily N Applied
- + Hundreds of factors

Insights | Potato Farm Yield Optimization

No Control

- Temperature (by hour)
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Insights | Potato Farm Yield Optimization

No Control

- Temperature (by hour)
- Humidity
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Control

- Daily NO_3 Applied
- Daily K Applied
- Daily P Applied
- Daily N Applied

+ Hundreds of factors

Insights | Potato Farm Yield Optimization

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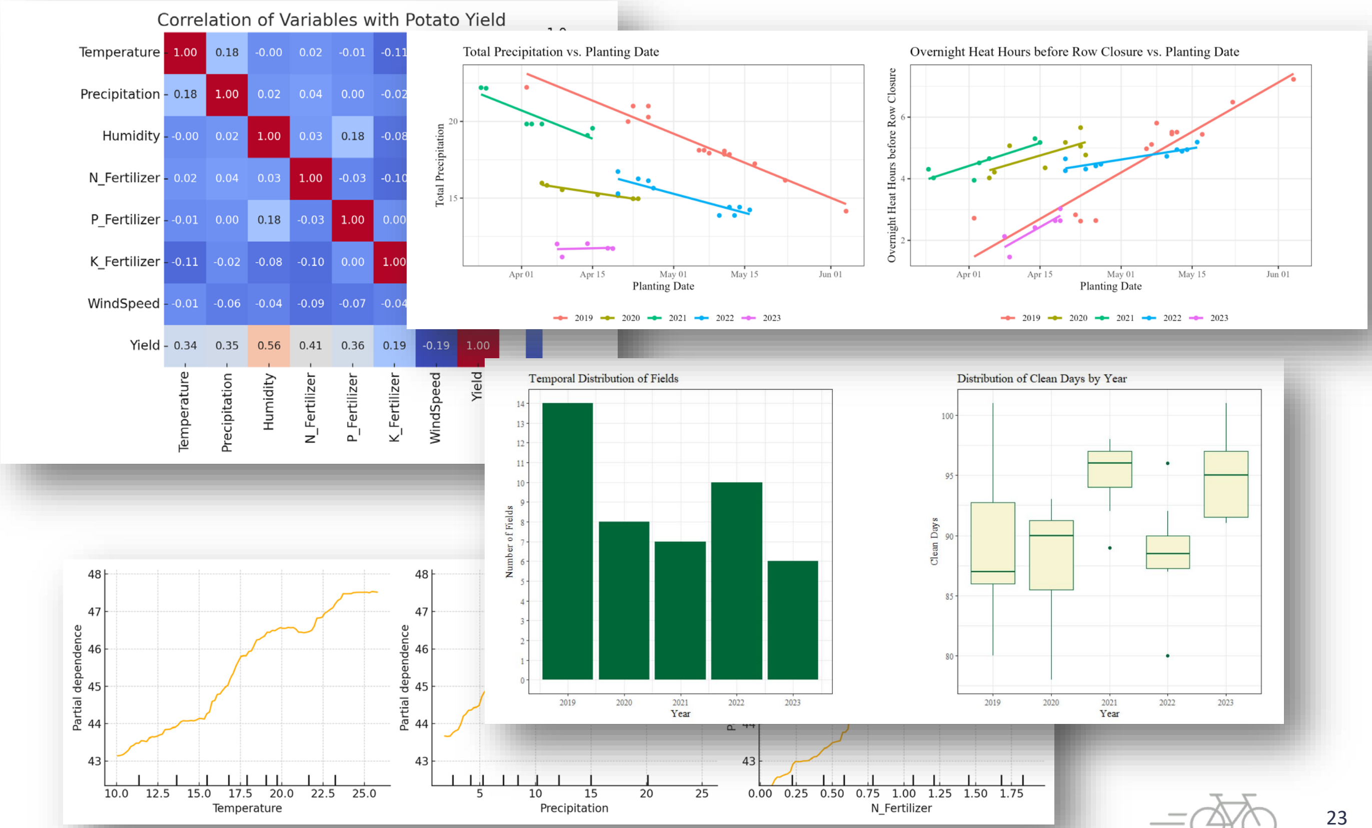
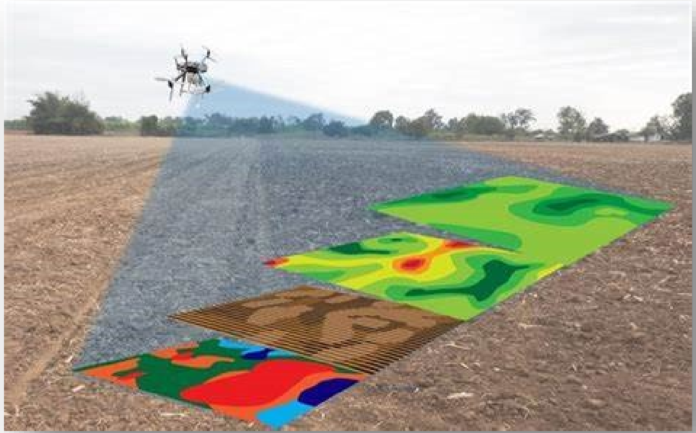
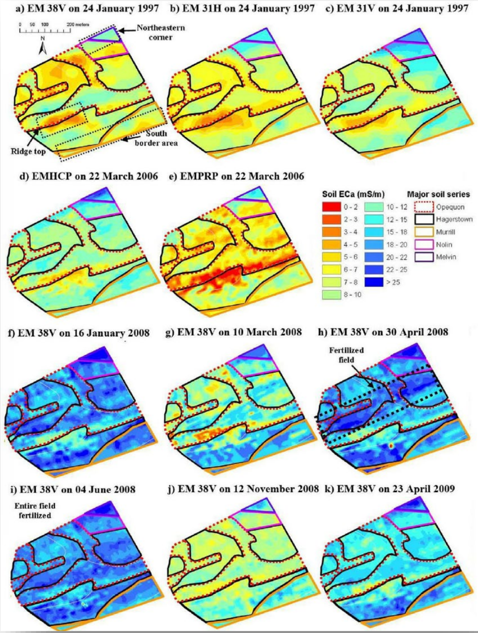


Insights | Potato Farm Yield Optimization

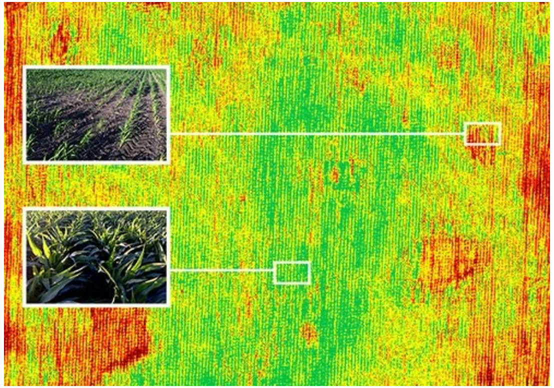
Advanced Measurement Techniques



Sensors & Software Inc. (2025), sensoft.ca



Lin & McBratney (2010), via ResearchGate



Croptracker (2023). Drone Technology in Agriculture. croptracker.com

Insights | Potato Farm Yield Optimization

Realtime Optimization

- ***Delay today's irrigation by 6 hours*** *to allow soil to absorb overnight precipitation and avoid oversaturation*
- *Apply* ***15% more nitrogen*** *to Field B this morning—levels are below optimal thresholds for the current growth stage.*
- *As of today (Day 45 of the season****), projected final yield is 46.2*** *tons per hectare, which is* ***3.5% above the 5-year average*** *for similar conditions.*

Insights | Potato Farm Yield Optimization

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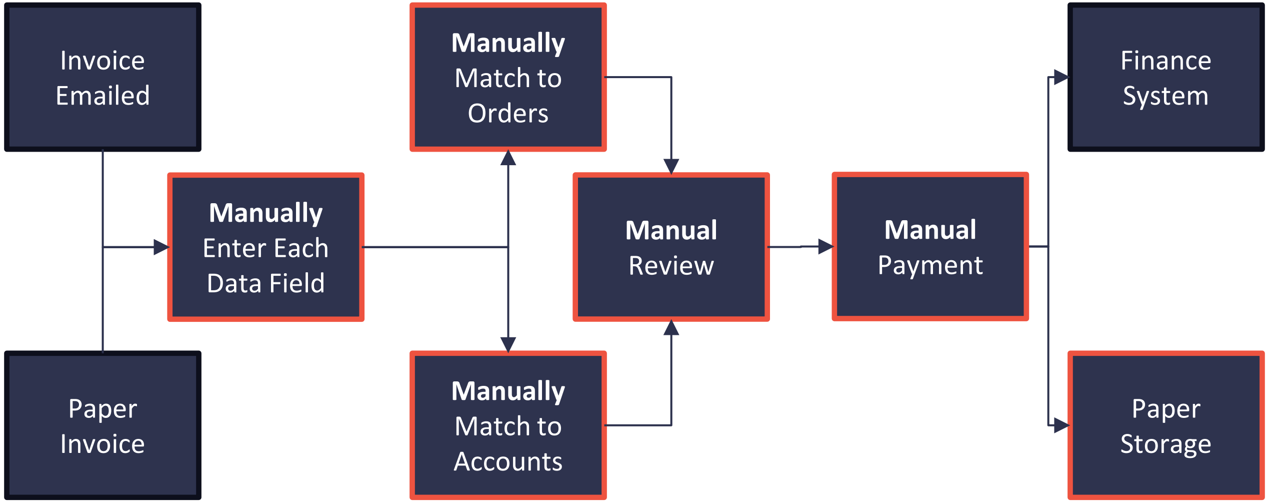
$50 Million

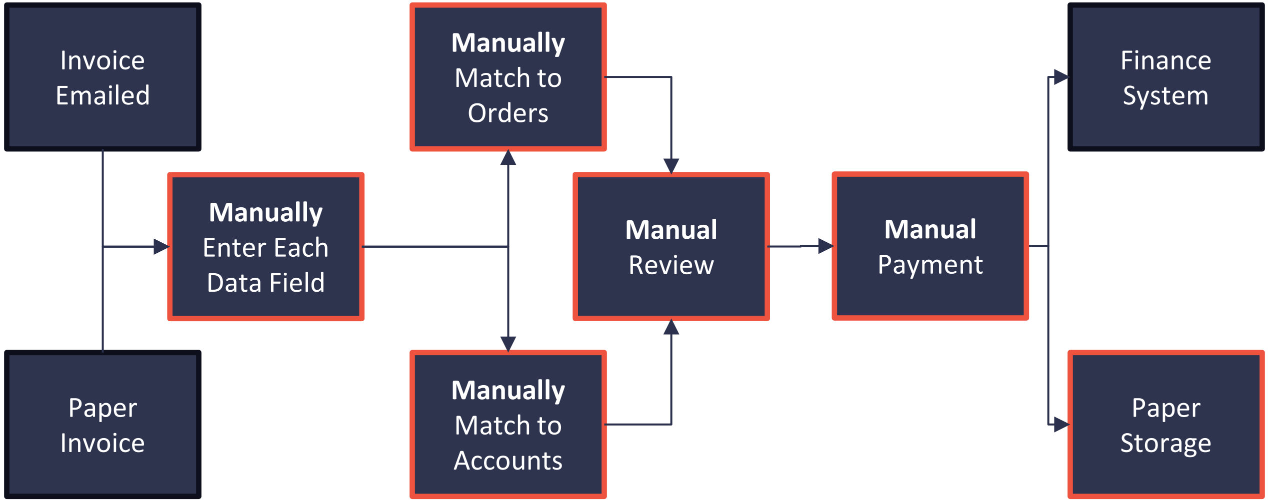
Suboptimal ⟷ Optimized

Automation

Automation | Accounts Payable



Automation | Accounts Payable

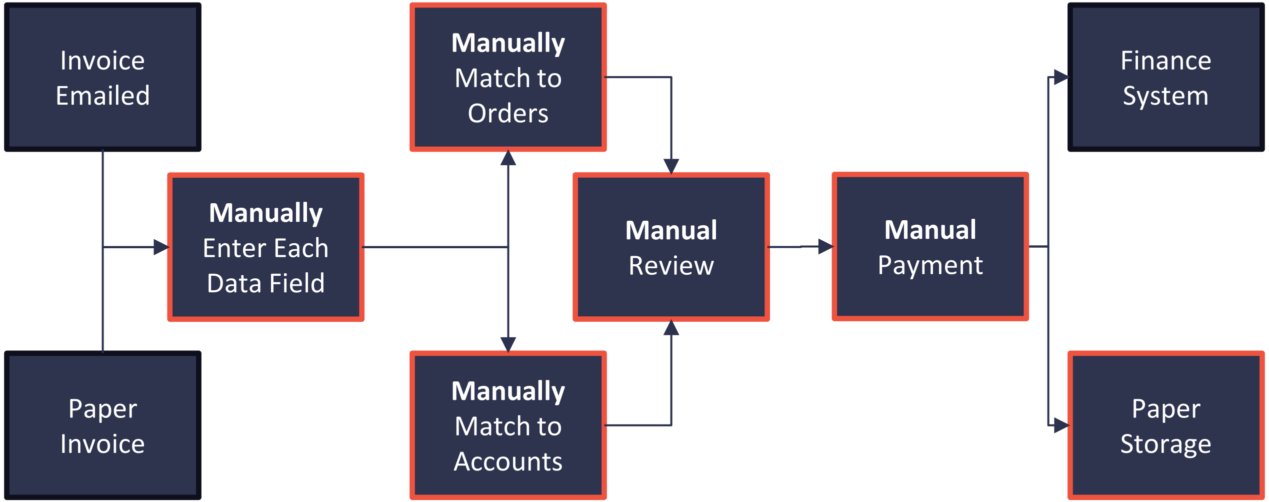


Data Inaccuracies and Errors

Limited Visibility and Control

Increased Fraud Risk and Compliance Challenges

Automation | Accounts Payable



Data Inaccuracies and Errors

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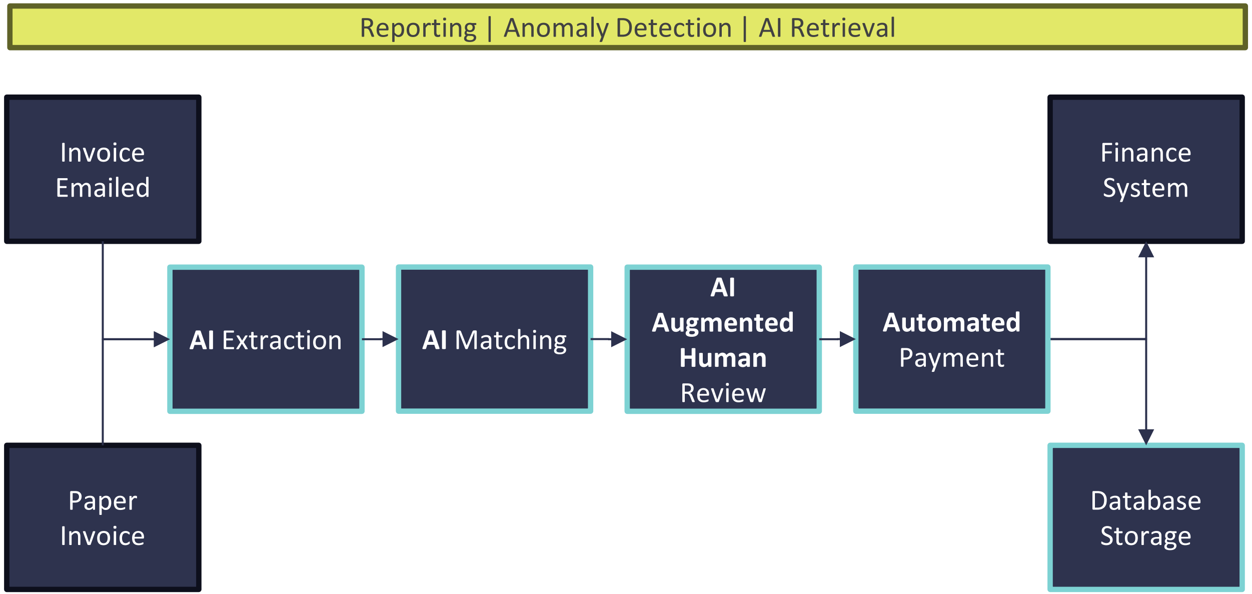
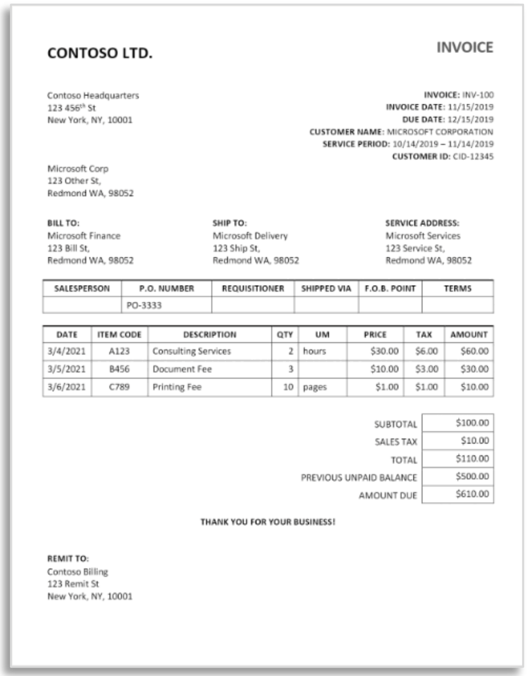
Increased Fraud Risk and Compliance Challenges

Medium-Sized Business Spends
15k-20k Hours/Year

Automation | Accounts Payable





CONTOSO LTD.

INVOICE

Contoso Headquarters
123 456th St
New York, NY, 10001

INVOICE: INV-100
INVOICE DATE: 11/15/2019
DUE DATE: 12/15/2019
CUSTOMER NAME: MICROSOFT CORPORATION
SERVICE PERIOD: 10/14/2019 – 11/14/2019
CUSTOMER ID: CID-12345

Microsoft Corp
123 Other St,
Redmond WA, 98052

BILL TO:
Microsoft Finance
123 Bill St,
Redmond WA, 98052

SHIP TO:
Microsoft Delivery
123 Ship St,
Redmond WA, 98052

SERVICE ADDRESS:
Microsoft Services
123 Service St,
Redmond WA, 98052

SALESPERSON	P.O. NUMBER	REQUISITIONER	SHIPPED VIA	F.O.B. POINT	TERMS
	PO-3333				

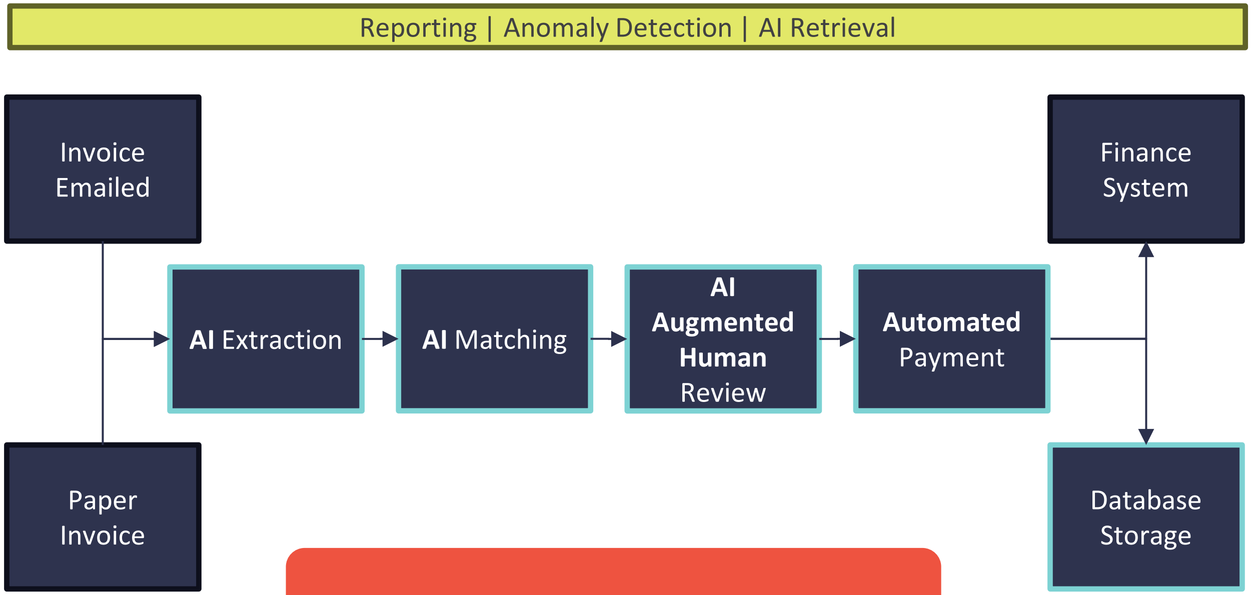
DATE	ITEM CODE	DESCRIPTION	QTY	UM	PRICE	TAX	AMOUNT
3/4/2021	A123	Consulting Services	2	hours	$30.00	$6.00	$60.00
3/5/2021	B456	Document Fee	3		$10.00	$3.00	$30.00
3/6/2021	C789	Printing Fee	10	pages	$1.00	$1.00	$10.00

SUBTOTAL	$100.00
SALES TAX	$10.00
TOTAL	$110.00
PREVIOUS UNPAID BALANCE	$500.00
AMOUNT DUE	$610.00

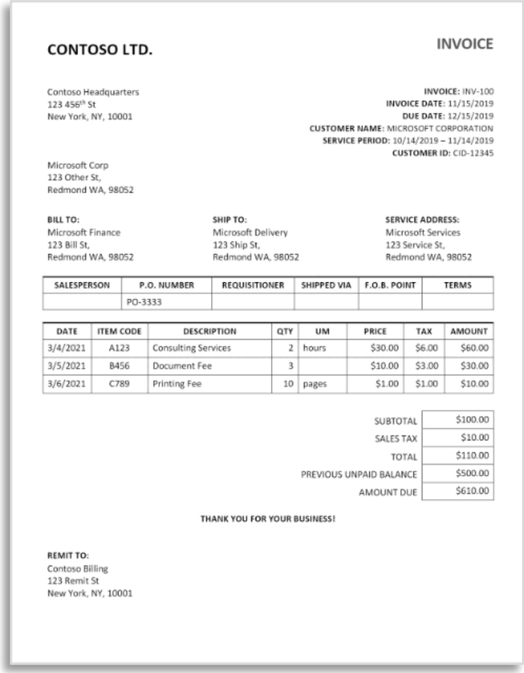
THANK YOU FOR YOUR BUSINESS!

REMIT TO:
Contoso Billing
123 Remit St
New York, NY, 10001

Automation | Accounts Payable



Medium-Sized Business **Saves**
$1.2 million – $1.6 million <u>Annually</u>



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Example: Pricing

Pricing Issues

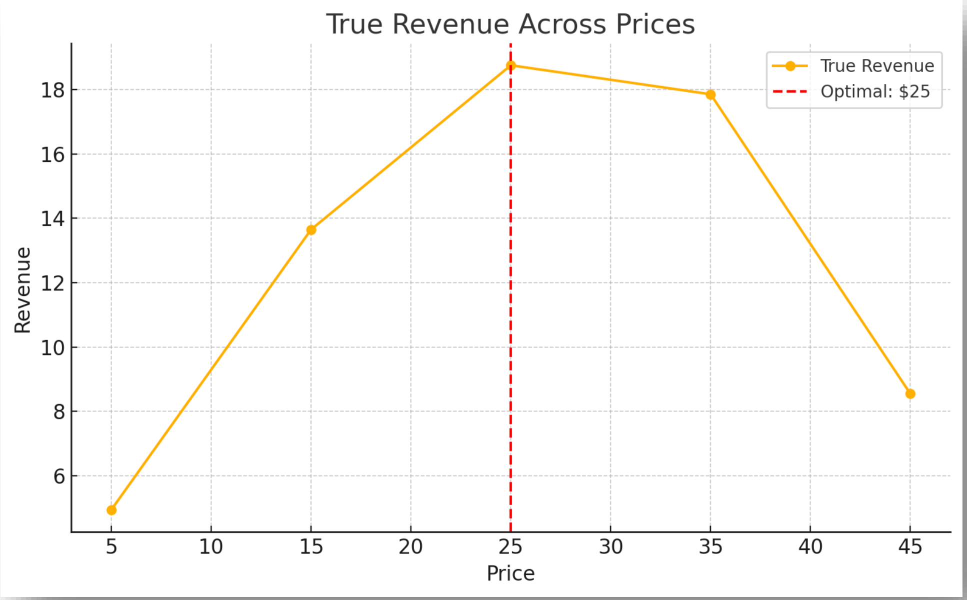
- Market Responsiveness
- Revenue Loss
- Inventory Imbalances
- Operational Inefficiency

Poll

Who has used Uber or Lyft?

Dynamic Pricing

- Thompson Sampling
  - Bayesian algorithm to test prices and converge on the optimal price
- Simulation Demo
  - Let’s test 5 price points



Dynamic Pricing

- **Reality**: Deep Reinforcement Learning
  - Continuous range of prices
  - Include wide range of market conditions
- Real-Time Price Adjustments
- Maximized Revenue Capture
- Optimized Inventory Management
- Impact: >$10M for medium-sized companies

Example:
Extraction & Classification

Manual Data Extraction

- High Manual Effort
- Risk of Errors & Inconsistencies
- Delayed Turnaround
- Operational Inefficiencies
- Scalability & Compliance Risks

Document Computer Vision

- Large Document Models
  - LayoutLMv3
  - Fine-tuned for specific documents
- Large Language Vision Models (LLVM)
  - GPT4o, LLaVA

arXiv:2304.08485v2 [cs.CV] 11 Dec 2023

Visual Instruction Tuning

Haotian Liu[1*], Chunyuan Li[2*], Qingyang Wu[3], Yong Jae Lee[1]
[1]University of Wisconsin–Madison [2]Microsoft Research [3]Columbia University
https://llava-vl.github.io

Abstract

Instruction tuning large language models (LLMs) using machine-generated instruction-following data has been shown to improve zero-shot capabilities on new tasks, but the idea is less explored in the multimodal field. We present the first attempt to use language-only GPT-4 to generate multimodal language-image instruction-following data. By instruction tuning on such generated data, we introduce LLaVA: **L**arge **L**anguage **a**nd **V**ision **A**ssistant, an end-to-end trained large multimodal model that connects a vision encoder and an LLM for general-purpose visual and language understanding. To facilitate future research on visual instruction following, we construct two evaluation benchmarks with diverse and challenging application-oriented tasks. Our experiments show that LLaVA demonstrates impressive multimodal chat abilities, sometimes exhibiting the behaviors of multimodal GPT-4 on unseen images/instructions, and yields a 85.1% relative score compared with GPT-4 on a synthetic multimodal instruction-following dataset. When fine-tuned on Science QA, the synergy of LLaVA and GPT-4 achieves a new state-of-the-art accuracy of 92.53%. We make GPT-4 generated visual instruction tuning data, our model, and code publicly available.

1 Introduction

Humans interact with the world through many channels such as vision and language, as each individual channel has a unique advantage in representing and communicating certain concepts, and thus facilitates a better understanding of the world. One of the core aspirations in artificial intelligence is to develop a general-purpose assistant that can effectively follow multi-modal vision-and-language instructions, aligned with human intent to complete various real-world tasks in the wild [4, 27, 26].

To this end, the community has witnessed an emergent interest in developing language-augmented foundation vision models [27, 16], with strong capabilities in open-world visual understanding such as classification [40, 21, 57, 54, 39], detection [29, 62, 33], segmentation [25, 63, 58] and captioning [50, 28], as well as visual generation and editing [42, 43, 56, 15, 44, 30]. We refer readers to the *Computer Vision in the Wild* reading list for a more up-to-date literature compilation [12]. In this line of work, each task is solved independently by one single large vision model, with the task instruction implicitly considered in the model design. Further, language is only utilized to describe the image content. While this allows language to play an important role in mapping visual signals to language semantics—a common channel for human communication, it leads to models that usually have a fixed interface with limited interactivity and adaptability to the user's instructions.

Large language models (LLM), on the other hand, have shown that language can play a wider role: a universal interface for a general-purpose assistant, where various task instructions can be explicitly represented in language and guide the end-to-end trained neural assistant to switch to the task of interest to solve it. For example, the recent success of ChatGPT [35] and GPT-4 [36] have demonstrated the power of aligned LLMs in following human instructions, and have stimulated tremendous interest in developing open-source LLMs. Among them, LLaMA [49] is an open-source LLM that matches the performance of GPT-3. Alpaca [48], Vicuna [9], GPT-4-LLM [38]

37th Conference on Neural Information Processing Systems (NeurIPS 2023).

Document Computer Vision

Potentially **Millions** of Manual Hours Saved Annually

Significant Reduction in Errors

Focus on High-Value Tasks

Enhanced Employee Well-Being

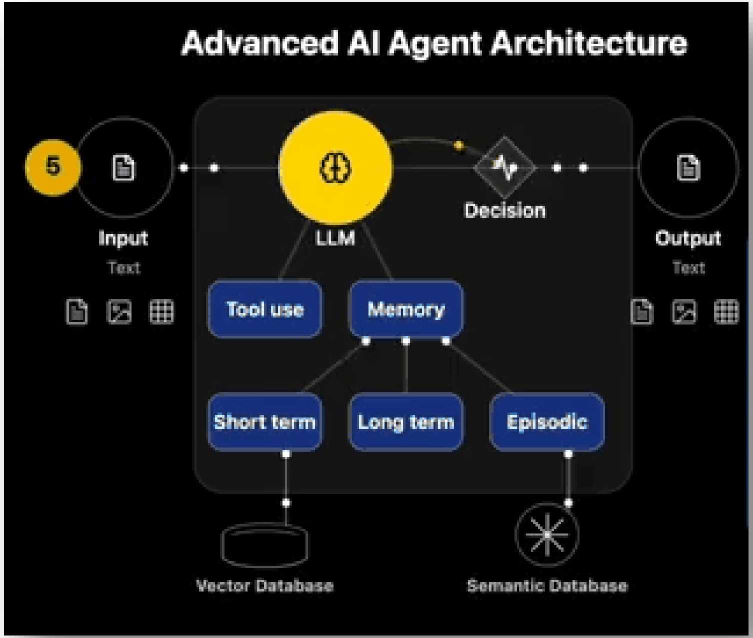
Example:
AI Agents

Poll

Who has used ChatGPT or other GenAI Tools?

AI Agents

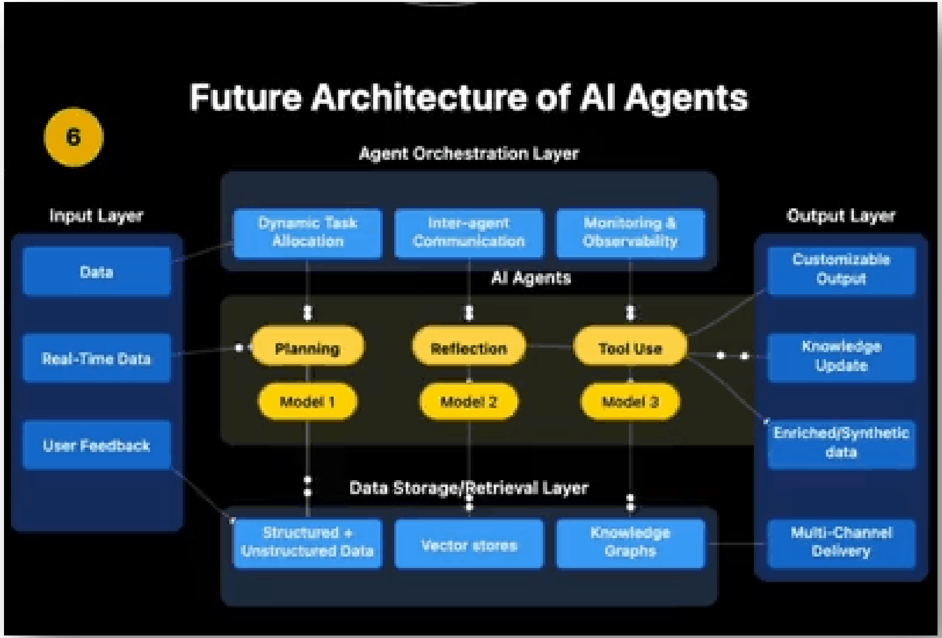
- Tools
  - Document AI for extraction/ classification
  - Python for calculations
  - Email
  - Human assistance
- Data
  - Structured
  - Unstructured



Source: Manthan Patel, *The evolution of AI Agents in 6 Key Phases*, LinkedIn, March 2025.

Future of AI Agents

- Multi-agent teams
  - Planner
  - Coder
  - Tester
  - Debugger
  - Architect
  - Product Owner



Source: Manthan Patel, *The evolution of AI Agents in 6 Key Phases*, LinkedIn, March 2025.

Final Thoughts

An interesting anecdote

Large Language Models Pass the Turing Test

Cameron R. Jones
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Benjamin K. Bergen
Department of Cognitive Science
UC San Diego
San Diego, CA 92119
bkbergen@ucsd.edu

Abstract

We evaluated 4 systems (ELIZA, GPT-4o, LLaMa-3.1-405B, and GPT-4.5) in two randomised, controlled, and pre-registered Turing tests on independent populations. Participants had 5 minute conversations simultaneously with another human participant and one of these systems before judging which conversational partner they thought was human. When prompted to adopt a humanlike persona, GPT-4.5 was judged to be the human 73% of the time: significantly more often than interrogators selected the real human participant. LLaMa-3.1, with the same prompt, was judged to be the human 56% of the time—not significantly more or less often than the humans they were being compared to—while baseline models (ELIZA and GPT-4o) achieved win rates significantly below chance (23% and 21% respectively). The results constitute the first empirical evidence that any artificial system passes a standard three-party Turing test. The results have implications for debates about what kind of intelligence is exhibited by Large Language Models (LLMs), and the social and economic impacts these systems are likely to have.

AI *won't* replace people.

AI *won't* replace people.

People with AI will replace people.

Questions?

CLAconnect.com

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