



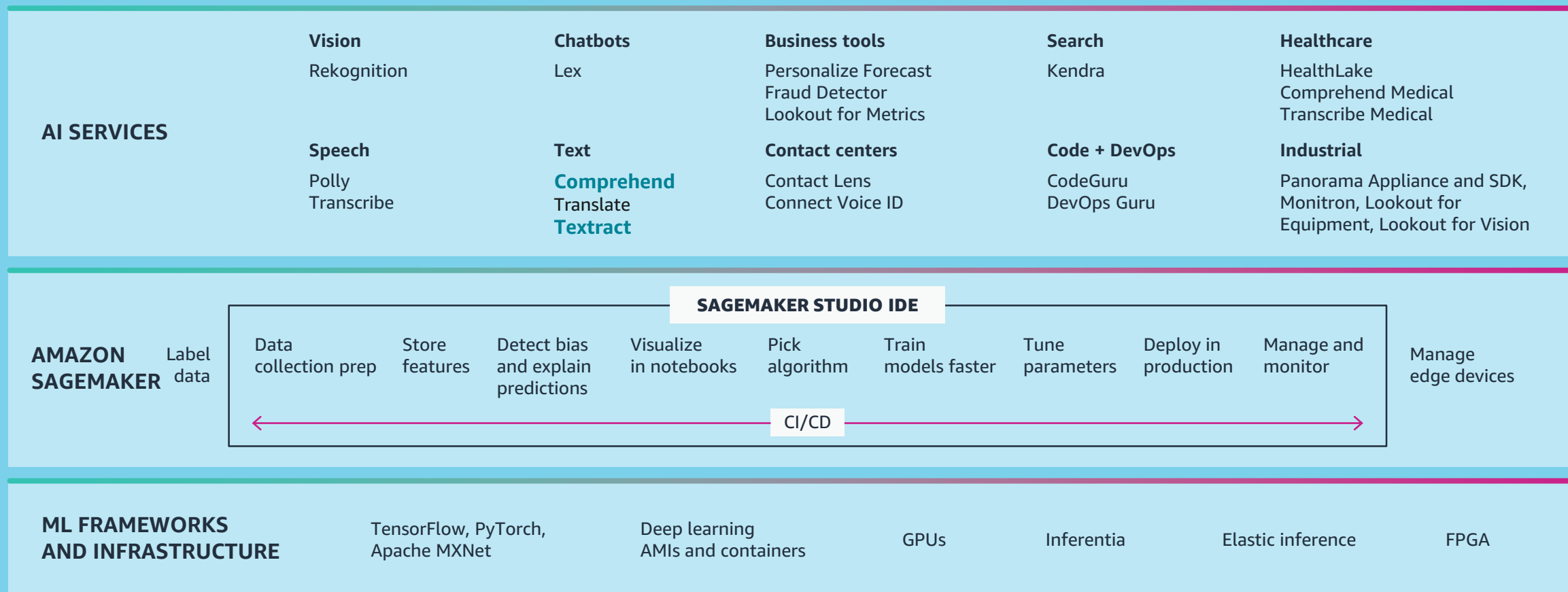
AI Workflow Automation for Document Processing

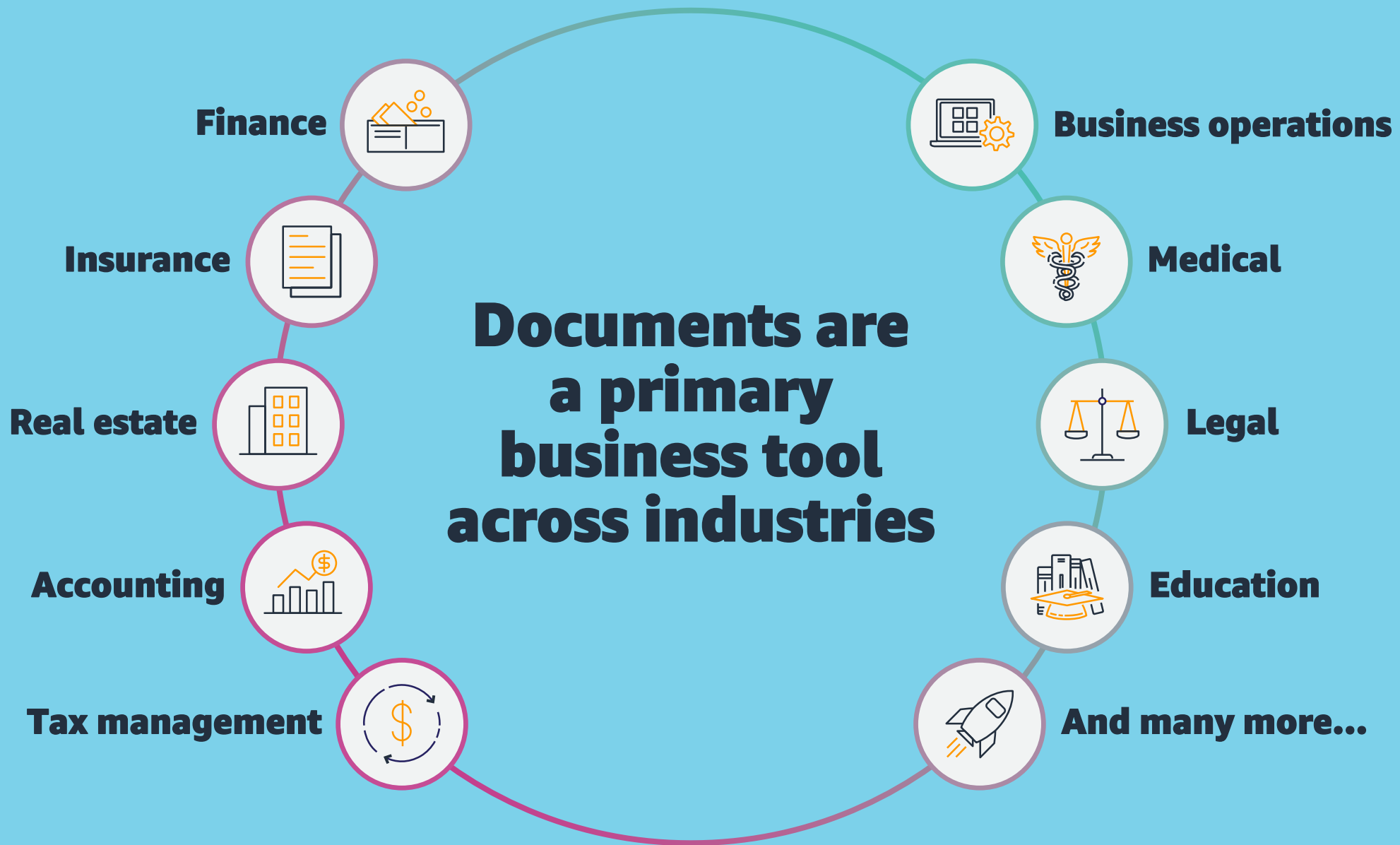
Raj Pathak

Solutions Architect, Amazon Web Services

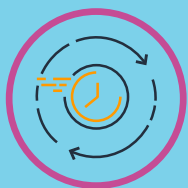
The AWS ML stack

Broadest and most complete set of machine learning capabilities





How documents are processed today



Manual processing

- ⊗ **Expensive**
- ⊗ **Error prone**
- ⊗ **Time consuming**



Traditional Optical Character Recognition (OCR)

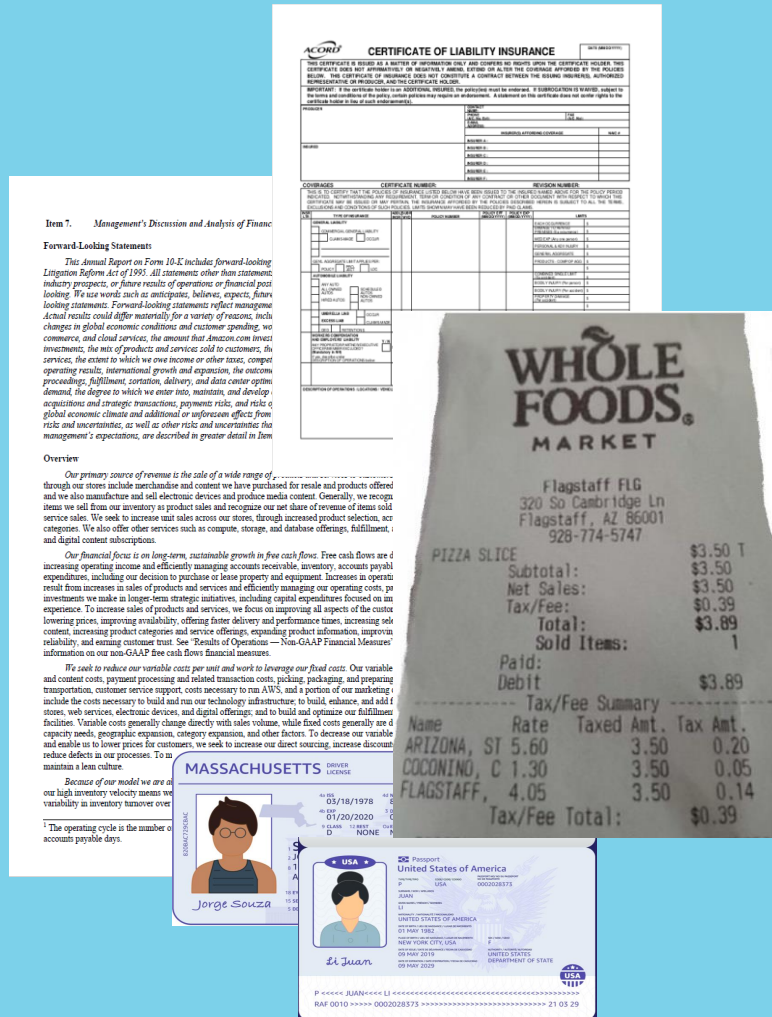
- ⊗ **Simple documents only**
- ⊗ **Error prone**
- ⊗ **Dump of text**



Rules and template-based extraction

- ⊗ **Limited by OCR accuracy**
- ⊗ **Development and management overhead**
- ⊗ **Templates are brittle**

Why do these challenges exist



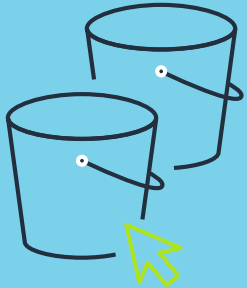
Documents are varied, and requirements for data are unique

Simply extracting data has become table stakes, adding insights and structure is what will provide organizations value from their documents

Solving these challenges with Intelligent Document Processing

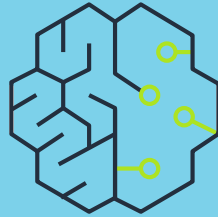
Let's start by modelling the process into there unique phases of the document processing lifecycle

Ingestion



Ingest documents into centralized document repository from different sources (email, upload, fax, scan etc.)

Extraction & Classification



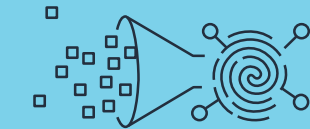
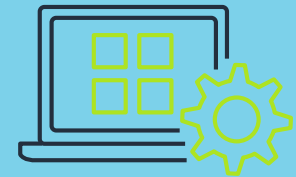
Extract data and classify documents

Post-Processing and Transformation



Validate and transform results from extraction into system ready requests

Storage and Workflow Automation



Ingest data into backend systems for storage or workflow automation

Ingestion

The first step in the IDP lifecycle, ingestion allows us to store the document, and tag it with the appropriate metadata preparing it for processing



Digital Upload



Email or Fax



Document Scan



Amazon S3

Using Amazon S3 as a landing zone for documents allows us to

- Tag documents with important metadata (timestamp, sender, document format) with Amazon S3 Object Tagging
- Allows for versioning and encryption of documents
- Provides low cost of storage, and storage tiering for archival data
- 11 9's of data durability
- WORM configurations can be applied to documents
- Built in integrations to AWS Services

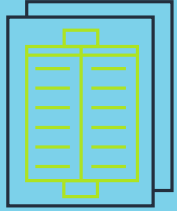
Extraction & Classification

The next step in our IDP workflow, Extraction and Classification, we will extract data off different documents and classify our results

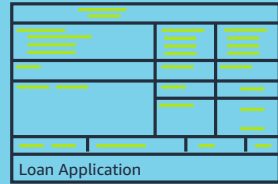


Using Amazon Textract will allow **for extraction of data from complex documents** and Amazon Comprehend will allow for **granular classification and insight generation** from extracted data

Amazon Textract capabilities

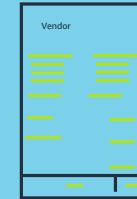


Text

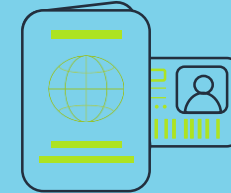


Forms

Invoices
and receipts



Identity
documents



**Specialized
documents**



Handwriting



Tables

Text extraction

Optimal for dense text extraction with industry leading OCR accuracy

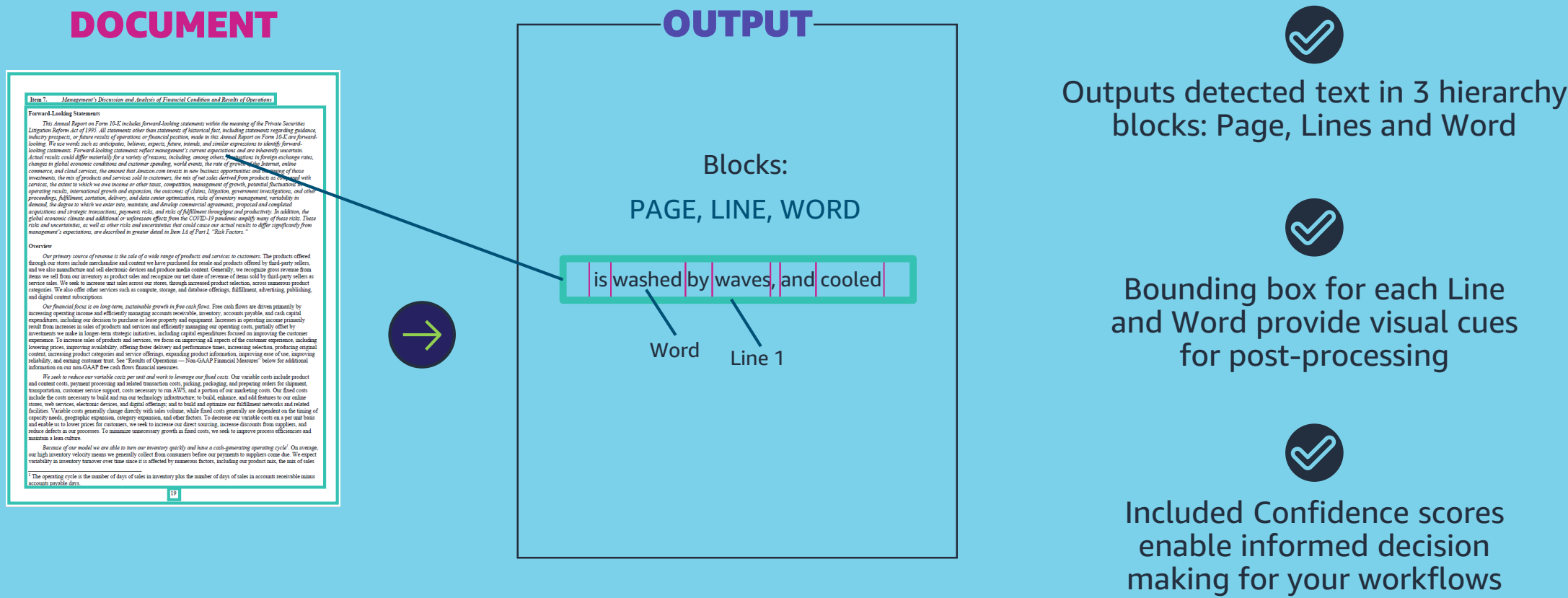


Table extraction

Extract tables from documents while preserving data structure and relationships

DOCUMENT

Previous employment history				
Start date	End date	Employer name	Position held	Reason for leaving
1/15/2009	6/30/2013	Any company	Head Baker	Family relocated
8/15/2013	Present	Example corp.	Baker	N/A, current employer



OUTPUT

Blocks:

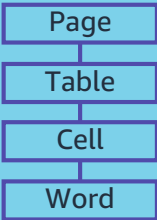
PAGE, TABLE, CELL

For each 'Block' you get:

TEXT

CONFIDENCE SCORE

BLOCK RELATIONSHIPS
(for example, cells within a table)



Outputs recognized tables with relationships data intact



Intelligently groups cells within tables and words within each cell



Output also includes confidence scores, geometry info, and row/column indexes

Form extraction

Extract form data from documents as key-value pairs to preserve document structure

DOCUMENT

Full Name		
John	X	Doe
First	Middle	Last

Date of Birth			Gender
01	01	1971	Male <input checked="" type="radio"/>
MM	DD	YYYY	Female <input type="radio"/>



OUTPUT

Blocks:

PAGE, KEY_VALUE_SET

Example Output:

First: John

Middle: X

Last: Doe

MM: 01

DD: 01

YYYY: 1971

Male: True

Female: False



Outputs form field name (Key) and field value name (Value) with relationship data intact



Captures logical groupings, relationships, and glyphs



Output also includes confidence scores, and geometry info

Invoices and receipts

Specialized support to process invoices and receipts at scale

DOCUMENT



OUTPUT

Summary Fields:
Vendor Name: WHOLE FOODS MARKET
Subtotal (SUBTOTAL): \$3.50
Net Sales (OTHER): \$3.50
Tax/Fee (TAX): \$0.39
Sold Items (OTHER): 1
Paid (OTHER):
Debit (OTHER): \$3.89
Tax/Fee Total (TAX): \$0.39
Total (TOTAL): \$3.89

Line Items:
ITEM: Pizza Slice
PRICE: \$3.50



Outputs headline amounts, line item details and inferred fields (like Vendor Name)



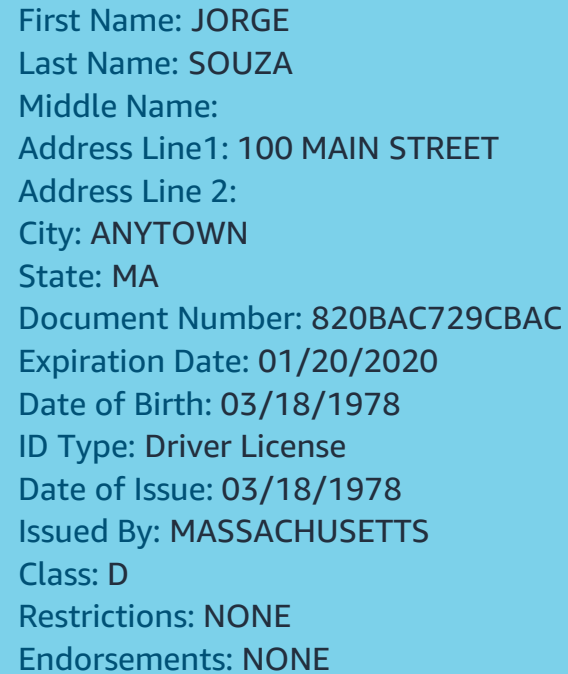
Supports any style of invoice or receipt



No templates or configuration required

NEW!

OUTPUT



95%+ accuracy for US driver licenses and passports



No templates or configuration required



Outputs normalized field names and supports implied elements

Amazon Comprehend IDP capabilities



**Named Entity
Recognition (NER)**



**Document
Classification**



**PII Detection and
Redaction**

Entity Detection

Amazon.com, Inc. is located in Seattle, WA and was founded July 5th, 1994 by Jeff Bezos. Known to the most customer obsessed organization, it welcomes thousands of customers and partners to one of its flagship events AWS re:Invent every year.

Amazon.com, Inc.	Entity: ORGANIZATION
Seattle, WA	Entity: LOCATION
July 5th, 1994	Entity: DATE
Jeff Bezos	Entity: PERSON
thousands of customers	Entity: QUANTITY
re:Invent	Entity: EVENT

Entities detected: Person, Organization, Location, Date, Quantity, Title, Commercial Item, Event, Other

Custom Entity Detection

Customize entity detection to your specific requirements by training an AutoNLP model



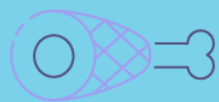
"I never received the shipment for part number **XT1764PY98**"

XT1764PY98: PART_NUMBER



"Trading of **ETFs** was halted today"

ETF: INVESTMENT_VEHICLE



"I liked the **shwarma** but loved the **hummus**"

shwarma, humus: MENU_ITEMS

Custom Entity Detection with spatial information



Custom NER enhancements + document format support

Comprehend entity detection support for semi-structured documents

- Use positional and structural context in addition to natural language context to build NER Models
- Bullets, tables, forms, and more
- Don't have to develop 'flattening' strategies
- Pre-integrates Amazon Textract and Amazon Comprehend

OFFERING_PRICE

OFFERED_SHARES

Table of Contents

DILUTION

If you purchase units in this offering, you will experience dilution to the extent of the difference between the public offering price of the units (attributing no value to the warrants) and the net tangible book value per share of our common stock immediately after this offering.

Our net tangible book value as of June 30, 2017 was approximately \$15.9 million, or \$0.5589 per share of common stock. Net tangible book value per share is equal to our total tangible assets minus total liabilities, all divided by the number of shares of common stock outstanding as of June 30, 2017.

After giving effect to the sale of 3,265,309 units at a price of \$2.45 per unit, and after deducting our estimated placement agent fees and offering expenses payable by us, and attributing no value to the warrants, our as adjusted net tangible book value would have been approximately \$23.3 million, or approximately \$0.7357 per share of common stock, as of June 30, 2017. This represents an immediate increase in net tangible book value of approximately \$0.1768 per share to existing stockholders and an immediate dilution of approximately \$1.714 per share to new investors. The following table illustrates this calculation on a per share basis:

Public offering price per unit		\$ 2.45
Net tangible book value per share as of June 30, 2017	\$ 0.5589	
Increase per share attributable to this offering	\$ 0.1768	
As adjusted net tangible book value per share as of June 30, 2017, after giving effect to this offering		\$ 0.7357
Dilution per share to new investors		\$ 1.714

The foregoing table and discussion is based on 28,452,305 shares outstanding as of June 30, 2017 and excludes:

- 1,937,871 shares of our common stock subject to outstanding options having a weighted average exercise price of \$5.54 per share;
- 54,300 shares of our common stock subject to outstanding restricted stock units;
- 1,804,079 shares of our common stock reserved for future issuance pursuant to our existing stock option plan;
- 4,788,166 shares of our common stock that have been reserved for issuance upon exercise of outstanding warrants having a weighted average exercise price

sreg-4a18dd34-2344-49fb-ac83-a0e8205aa188_1

BLOCK

SHOW DOCUMENT

OFFERING_PRICE-SUBTYPE

HIDE

SELECT

PER_SHARE

SELECTED ENTITIES

COPY

REMOVE

OFFERING_PRICE

\$ 2.45

0

6

RESET

Custom Classification

Classify documents to your specific requirements by training an AutoNLP classification model



- Pricing
- Loyalty Program
- Technical Support



- Adventure
- Comedy
- Drama

Multi-class

- Classes are mutually exclusive
- Classification into one class
- Each model allows 1000 classes

Multi-label

- Classes are not mutually exclusive
- Classification into one or more classes
- Each model allows 100 unique classes

PII Detection

Hi, my name is John Doe. For verification, the last 4 digits of my social are 6789 and my dob is 01/01.

I paid for my credit card 1111-0000-1111-0000 last week from my bank account XXXXXX1111 with the routing number XXXXX0000. The check was mailed from 100 Main Street, Anytown, WA 98121.

Please confirm receipt by calling me at 206-555-0199 or emailing at john.doe@anycompany.com.

John Doe	Entity: NAME
6789	Entity: SSN
01/01	Entity: DATE_TIME
1111-0000-1111-0000	Entity: CREDIT_DEBIT_NUMBER
XXXXXX1111	Entity: BANK_ACCOUNT_NUMBER
XXXXX0000	Entity: BANK_ROUTING
100 Main Street, Anytown, WA 98121	Entity: ADDRESS
206-555-0199	Entity: PHONE
john.doe@anycompany.com	Entity: EMAIL

PII handling options: Detect, Redact, Mask

Detect

Hi, my name is John Doe. For verification, the last 4 digits of my social are 6789 and my dob is 01/01.

I paid for my credit card 1111-0000-1111-0000 last week from my bank account XXXXXX1111 with the routing number XXXXX0000. The check was mailed from 100 Main Street, Anytown, WA 98121.

Please confirm receipt by calling me at 206-555-0199 or emailing at john.doe@anycompany.com.

Redact

Hi, my name is [NAME]. For verification, the last 4 digits of my social are [SSN] and my dob is [DATE_TIME].

I paid for my credit card [CREDIT_DEBIT_NUMBER] last week from my bank account [BANK_ACCOUNT_NUMBER] with the routing number [BANK_ROUTING]. The check was mailed from [ADDRESS].

Please confirm receipt by calling me at [PHONE] or emailing at [EMAIL].

Mask

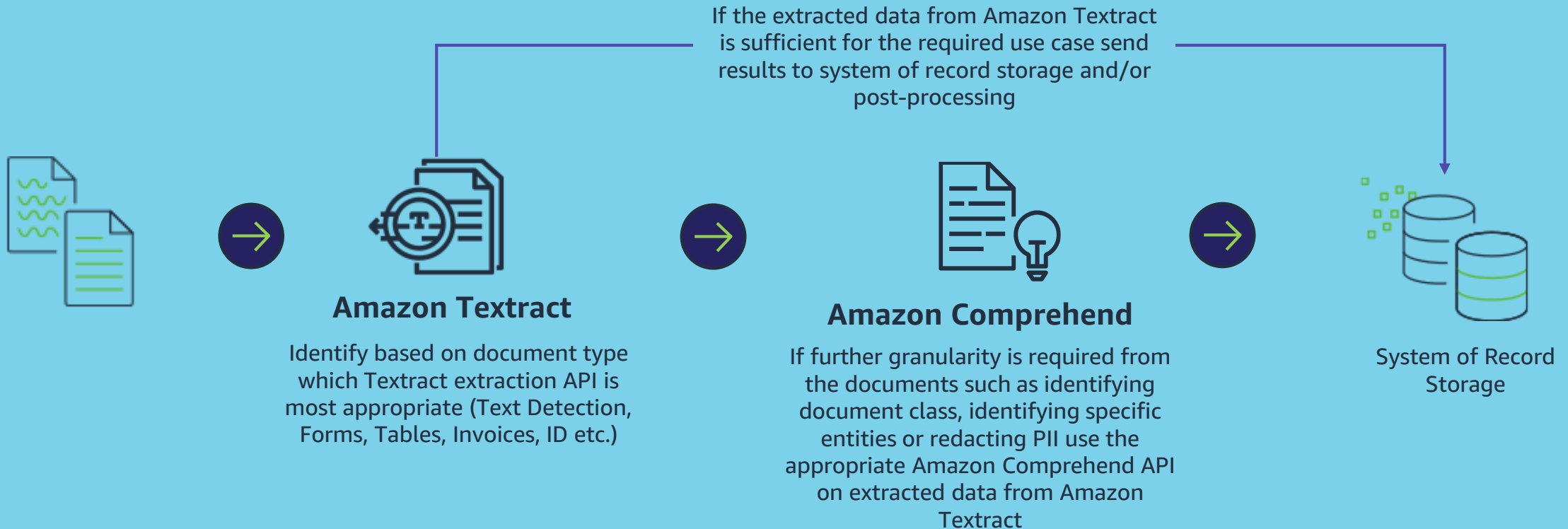
Hi, my name is *****. For verification, the last 4 digits of my social are **** and my dob is *****.

I paid for my credit card ***** last week from my bank account ***** with the routing number *****. The check was mailed from *****.

Please confirm receipt by calling me at ***** or emailing at *****.

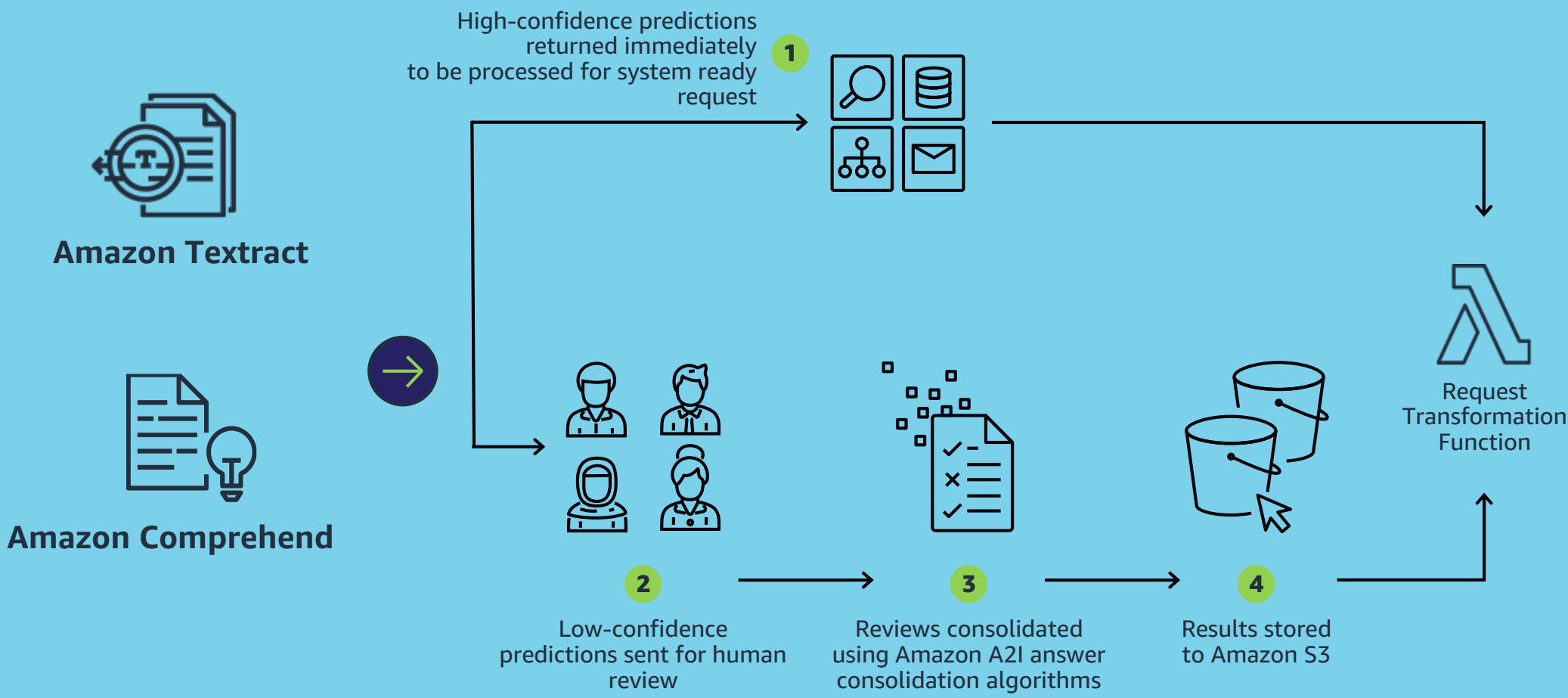
Putting it together

Let's understand where each API can be used as apart of our extraction and classification workflow



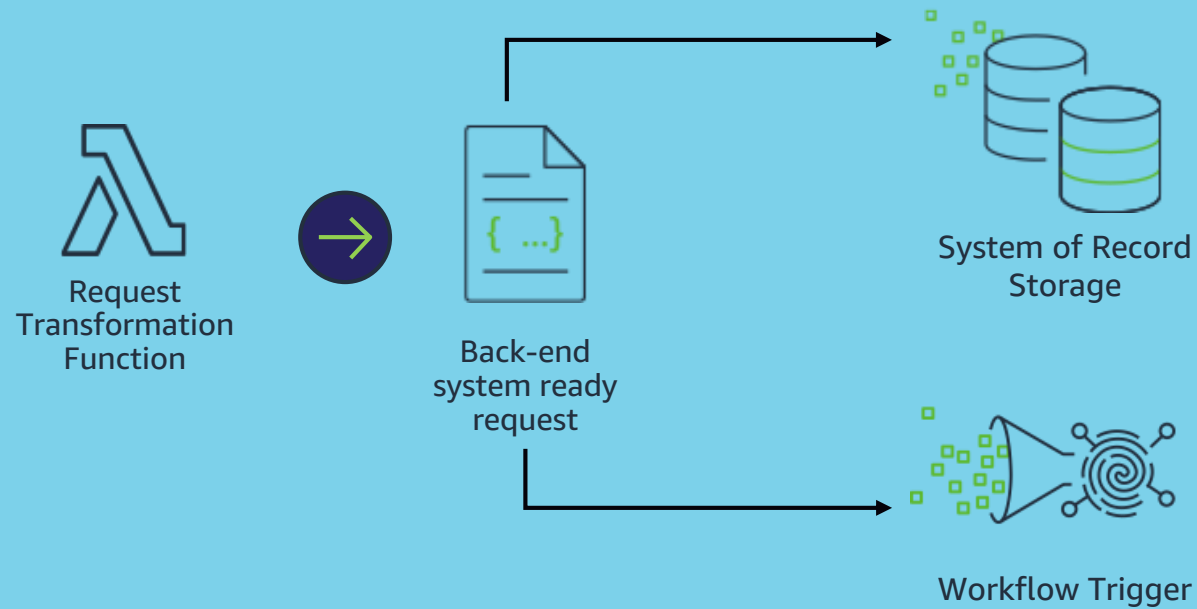
Post-Processing and Transformation

The next step in our IDP workflow, Post-Processing and Transformation, ensures our output data is of high quality and is ready to ingest into our back-end storage and workflows

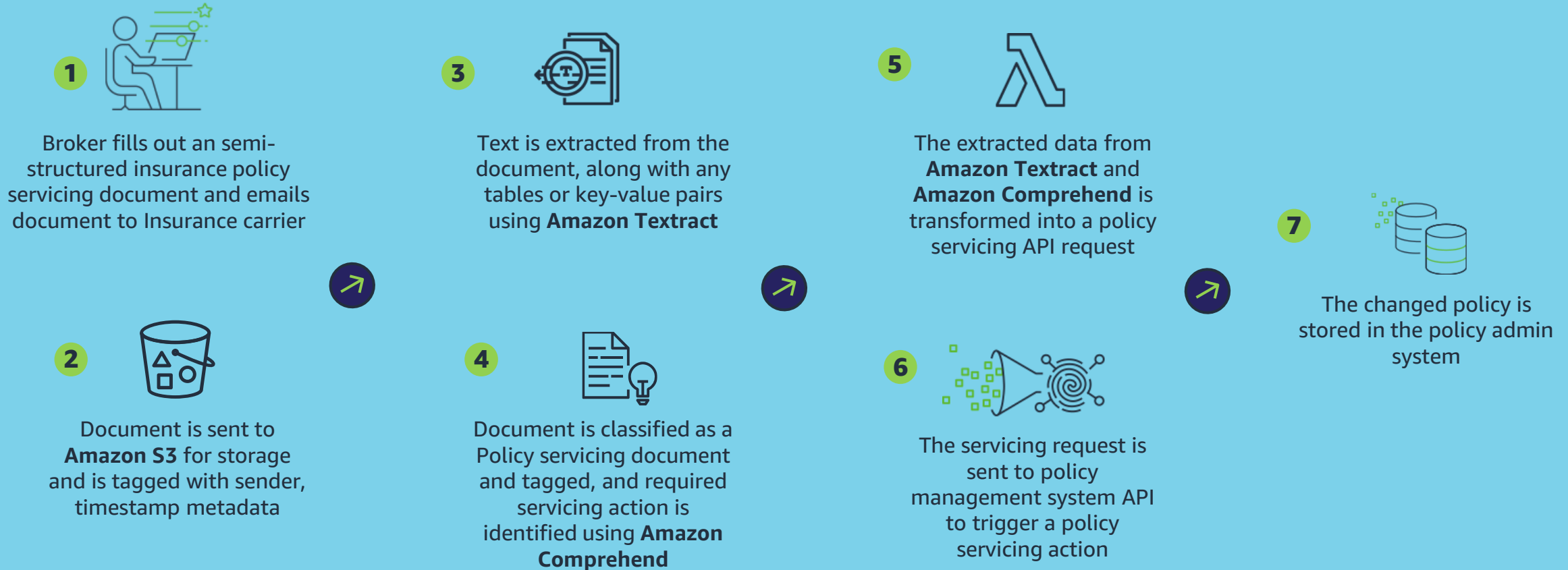


Storage and Workflow Automation

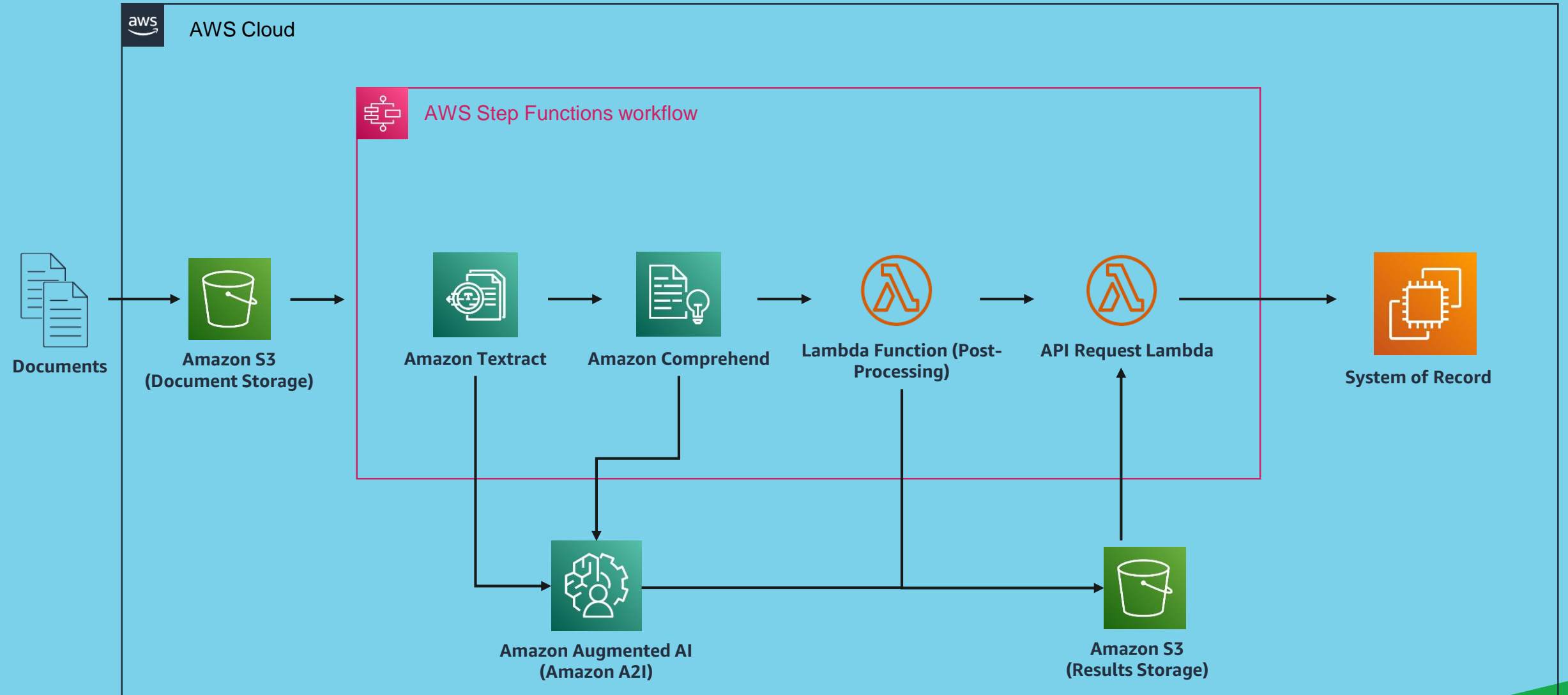
The final step in our IDP workflow, Storage and Workflow Automation, acts as the final stop for our document data, it is used to store the document in a system of record, or used to trigger back-end automation



An end to end IDP example visualized – Insurance Policy Servicing



AWS Reference Architecture IDP





Thank you!