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ALEPPO DEVELOPERS  
COMMUNITY

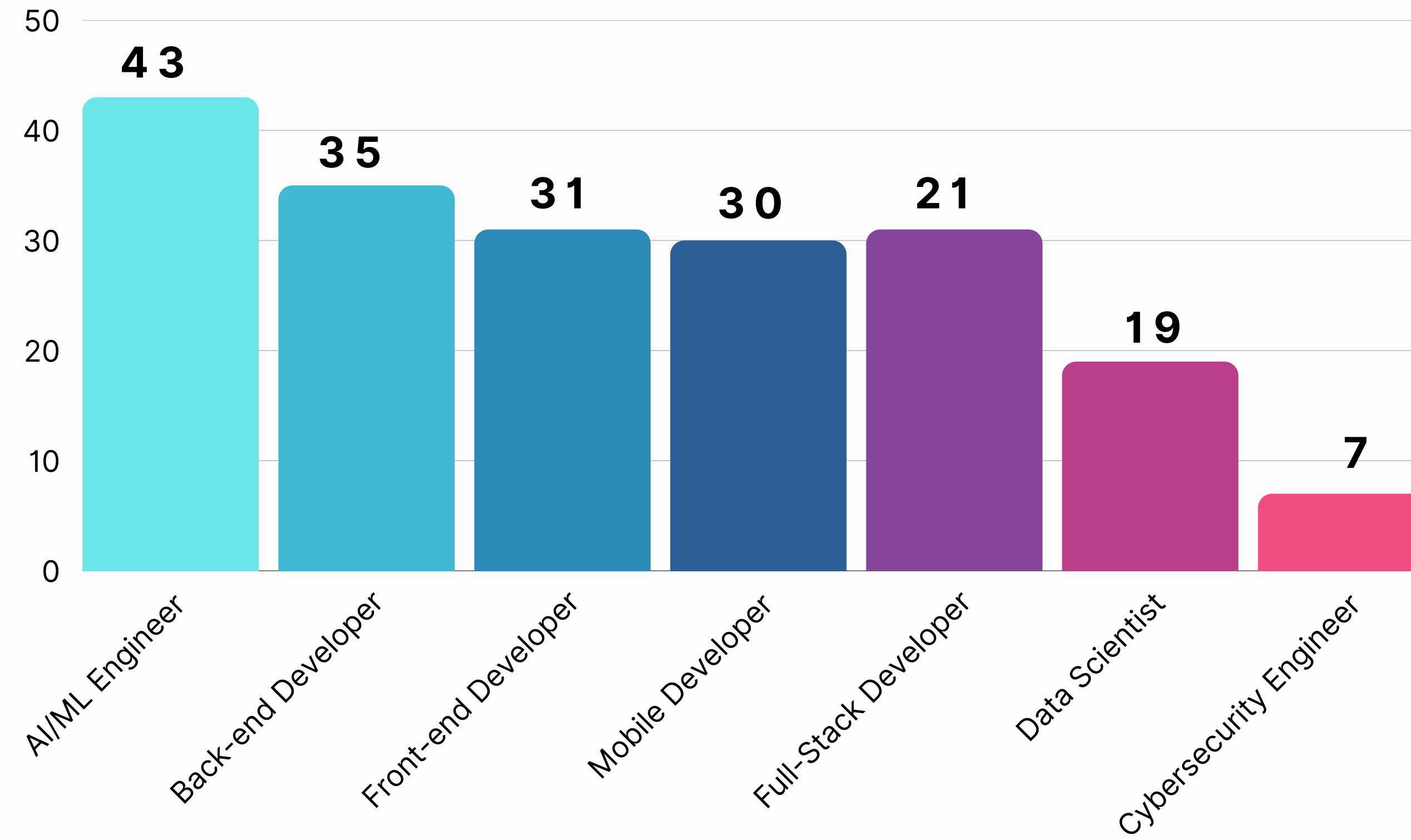
AI MEETUP - AUG 2025

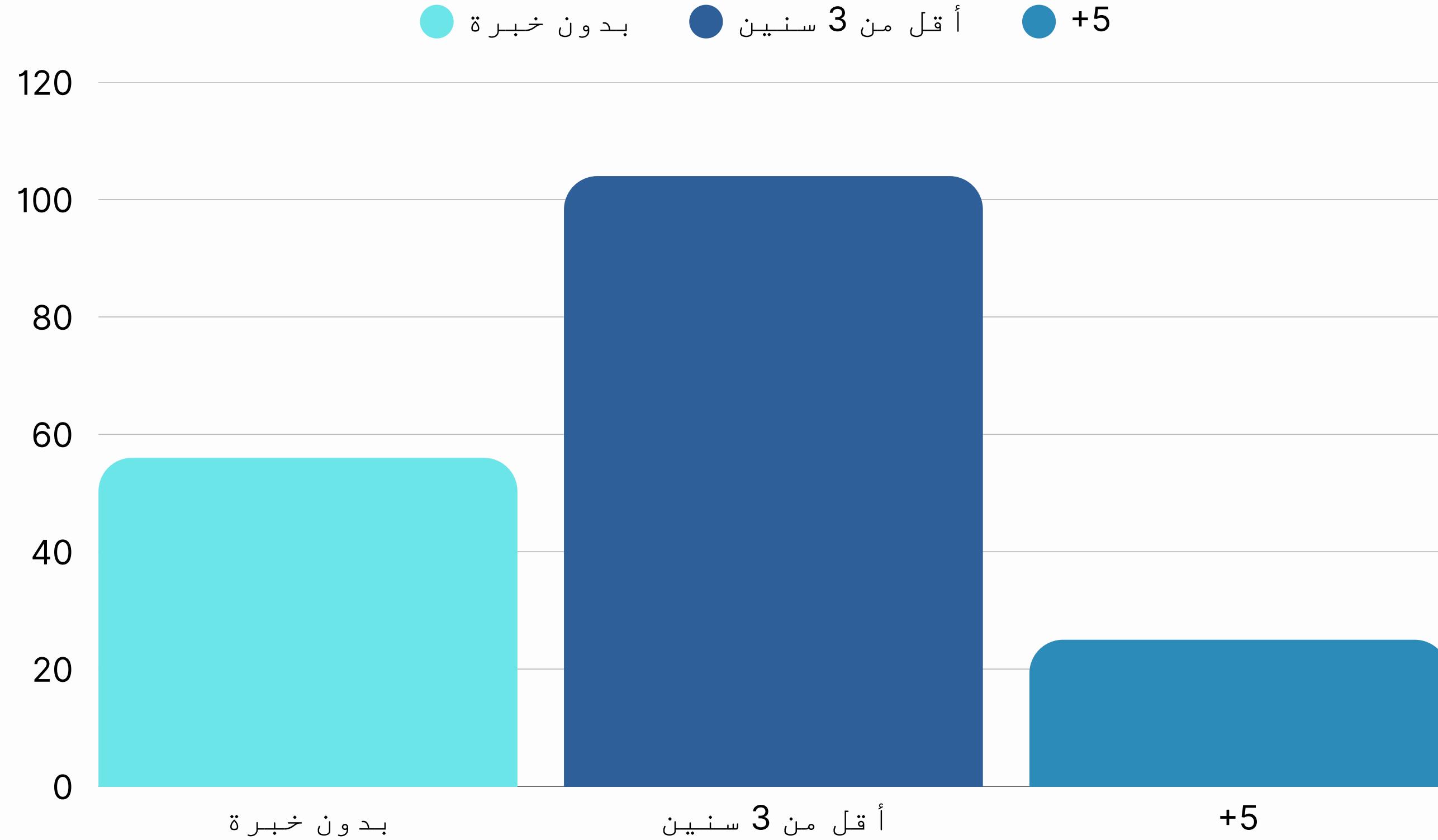


# OPENNING WORD



● AI/ML Engineer   ● Back-end Developer   ● Front-end Developer  
● Mobile Developer   ● Full-Stack Developer   ● Data Scientist  
● Cybersecurity Engineer





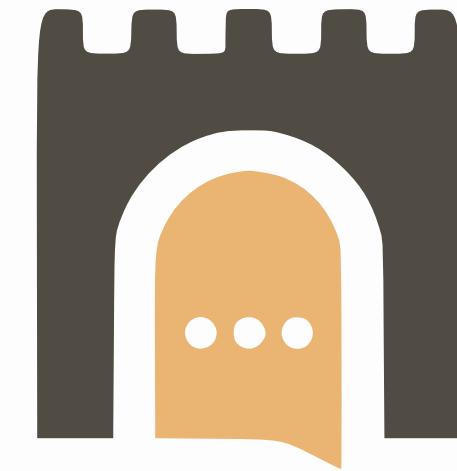


# ALAA ALDIN HAJJAR

PHD MATHEMATICAL MODELING & SOFTWARE SYSTEMS

“ CRAFTING AI SOLUTIONS  
WITH REAL BUSINESS VALUE ”





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NETWORKING  
BREAK



# ABD ULFATAH ESPER

AI ENGINEER, DATA SCIENTIST

“ SELF-ADAPTING LANGUAGE  
MODELS

”





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# Let's Build the Future of Aleppo's Tech Scene Together!

STAY CONNECTED!



# Crafting AI Solutions with Real Business Values

Alaa Aldin Hajjar

Aleppo Developers Community  
Second Meetup

August 9, 2025



# Contents

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1. Overview
2. Why a Standard Process?
3. Phase 1: Business Understanding
4. Phase 2: Data Understanding
5. Phase 3: Data Preparation
6. Phase 4: Modeling
7. Phase 5: Evaluation
8. Phase 6: Deployment
9. Summary

## **Overview**

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# Overview

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- Introduction to CRISP-DM
- Phases and Tasks
- Summary

## CRoss-Industry Standard Process for Data Mining

## **Why a Standard Process?**

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## Why Should There Be a Standard Process?

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The data mining process must be reliable and repeatable by people with little data mining background.

# Why a Standard Process?

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- Framework for recording experience
- Allows projects to be replicated
- Aid to project planning and management
- “Comfort factor” for new adopters
- Demonstrates maturity of Data Mining
- Reduces dependency on “stars”

# Process Standardization

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- Initiative launched in late 1996 by Daimler-Chrysler, SPSS, NCR
- Refined via workshops (1997–1999), > 300 organizations
- Published CRISP-DM 1.0 in 1999
- CRISP-DM SIG: > 200 members worldwide (vendors, consultants, end-users)

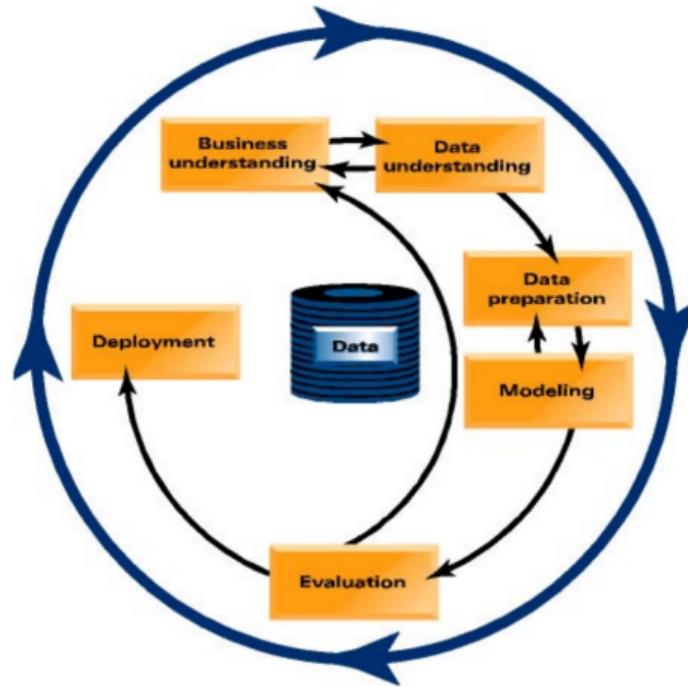
# Key Characteristics of CRISP-DM

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- Non-proprietary, tool-neutral, industry-neutral
- Focus on business as well as technical analysis
- Provides framework, templates and an experience base

## CRISP-DM: Phases

- Business Understanding
  - Data Understanding
  - Data Preparation
  - Modeling
  - Evaluation
  - Deployment



## **Phase 1: Business Understanding**

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# Phase 1: Business Understanding

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## Main Tasks

- Determine business objectives
- Assess situation
- Determine data mining goals
- Produce project plan

Converts business needs into a well-defined data mining problem and plan.

# Phase 1: Business Understanding

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## Determine business objectives

- What does the client really want?
- Prevent solving the wrong problem

## Assess situation

- Resources, constraints and assumptions
- Detailed fact-finding

# Phase 1: Business Understanding

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## Data mining goals

- Business goal in business terms
- Data mining goal in technical terms

## Project plan

- Steps, tools, techniques and schedule

## **Phase 2: Data Understanding**

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## Phase 2: Data Understanding

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- Collect initial data
- Describe data
- Explore data
- Verify data quality

Get familiar with the data, identify quality issues, and generate initial insights.

# Phase 2 Details

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## Collect / Describe Data

- Load data, integrate sources
- Examine “surface” properties

## Explore / Verify Quality

- Visualize distributions, correlations
- Detect missing values, outliers

## **Phase 3: Data Preparation**

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## Phase 3: Data Preparation

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- Select data (tables, records, attributes)
- Clean data (missing, outliers)
- Construct derived attributes
- Integrate and format for modeling

Typically > 90 % of project effort.

# Phase 3 Details

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## Select & Clean

- Relevance, quality, volume constraints
- Impute or remove bad data

## Construct & Integrate

- Derive new features
- Join tables, synthesize records

## **Phase 4: Modeling**

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## Phase 4: Modeling

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- Select modeling techniques
- Generate test design
- Build models
- Assess and compare models

Iteration with data preparation is common.

# Phase 4 Details

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## Select / Test Design

- Decision trees, neural nets, etc.
- Train / test split, cross-validation

## Build / Assess

- Calibrate parameters
- Rank by accuracy, ROC, business criteria

## **Phase 5: Evaluation**

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## Phase 5: Evaluation

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- Evaluate results against business objectives
- Review the entire process for gaps
- Decide next steps: deploy or iterate

Ensure the model solves the right problem before deploying.

# Phase 5 Details

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## Evaluate Results

- Technical metrics and business impact
- Test in real applications if possible

## Review Process

- QA steps, overlooked issues

## Next Steps

- Deployment or further iterations

## **Phase 6: Deployment**

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## Phase 6: Deployment

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- Plan deployment and monitoring
- Produce final report
- Review project lessons

Turn your data mining results into day-to-day business practice.

# Phase 6 Details

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## Deployment Plan

- Who uses results, how often, by what mechanism?

## Monitoring & Maintenance

- Ensure continued validity

## Reporting & Review

- Summarize findings, capture lessons learned

## **Summary**

---

# Summary

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## Why CRISP-DM?

- Reliable, repeatable process for all skill levels
- Uniform framework: guidelines + experience base
- Flexible to different businesses and data

# Thank you!

Questions?



# SELF ADAPTIVE LANGUAGE MODELS - SEAL

LANGUAGE MODELS THAT TEACH THEMSELVES

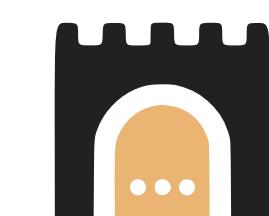
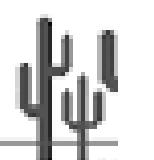


# REINFORCEMENT LEARNING

HI 002005 000025

**REINFORCEMENT LEARNING** IS A  
TYPE OF MACHINE LEARNING  
WHERE AN AGENT LEARNS TO  
MAKE DECISIONS BY  
INTERACTING WITH AN  
ENVIRONMENT AND RECEIVING  
REWARDS OR PENALTIES.

OVER TIME, IT IMPROVES ITS  
STRATEGY TO **MAXIMIZE** LONG-  
TERM REWARDS.



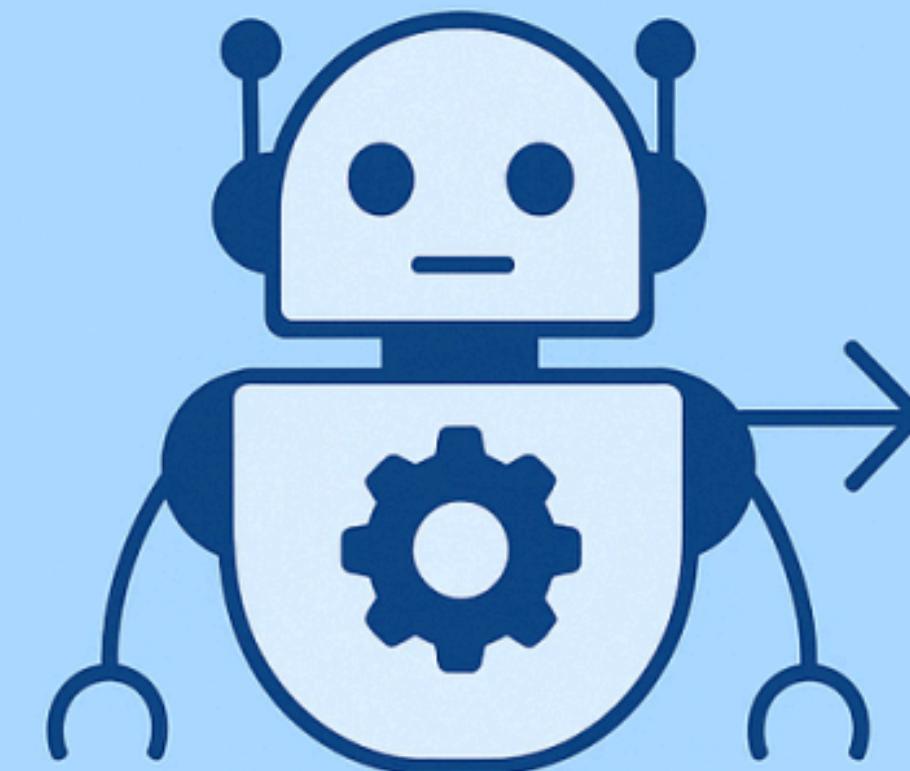
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# LLMS VS AI AGENTS

## ARE THEY THE SAME OR WORLDS APART?



LLM



Agentic AI

# THE PROBLEM

TRADITIONAL LLMS ARE STATIC  
AFTER TRAINING

HUMAN-CURATED FINE-TUNING  
DOES NOT SCALE

LIMITED ABILITY TO  
INCORPORATE NEW KNOWLEDGE

APPROACHING DATA QUALITY  
CEILING



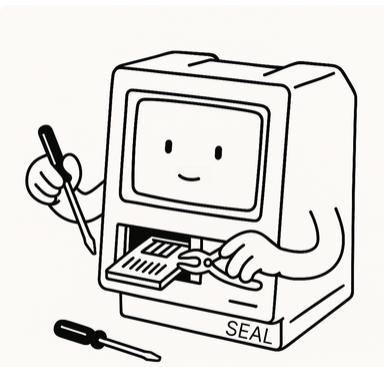
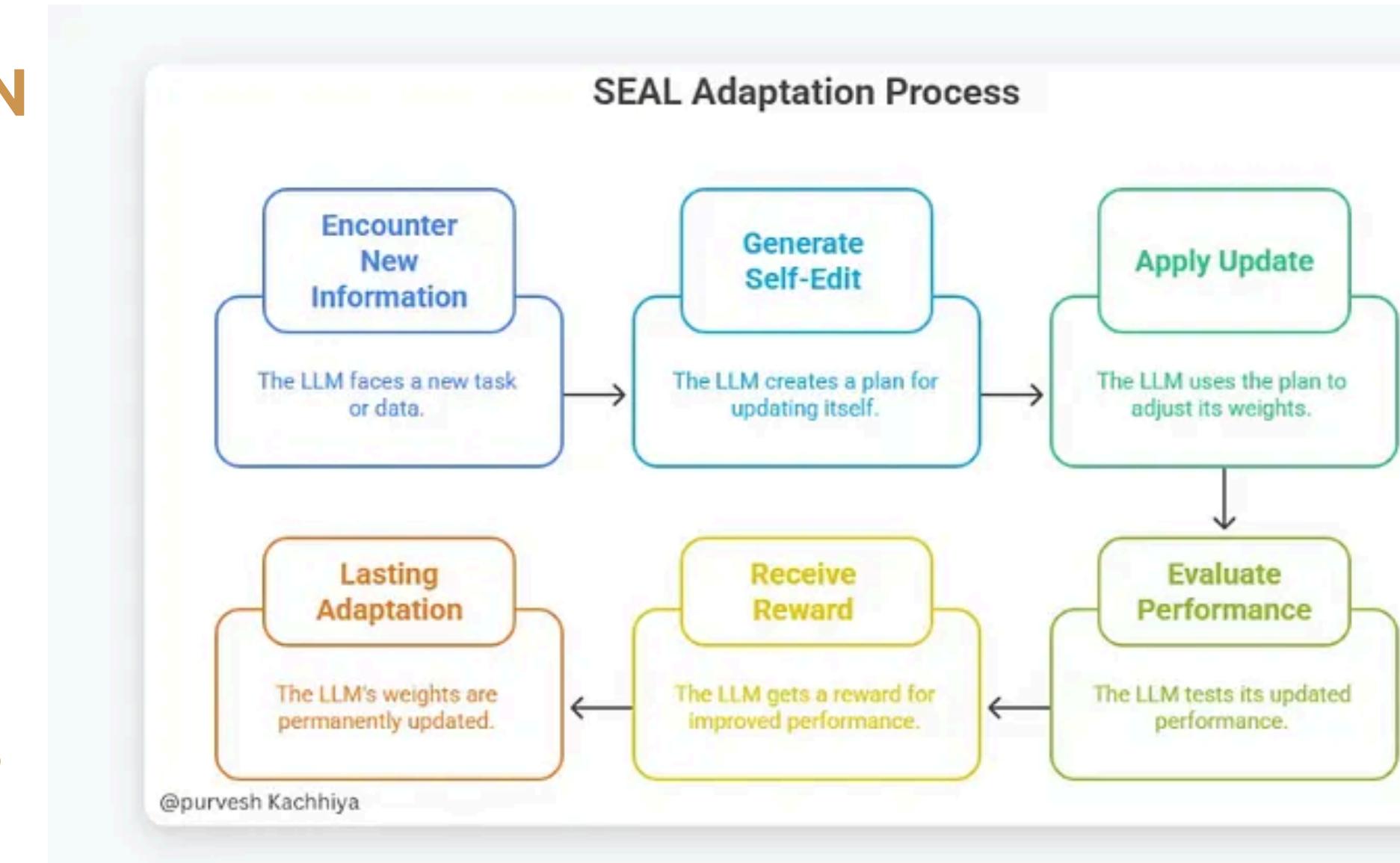
# INTRODUCING SEAL

## SELF ADAPTIVE LANGUAGE MODELS

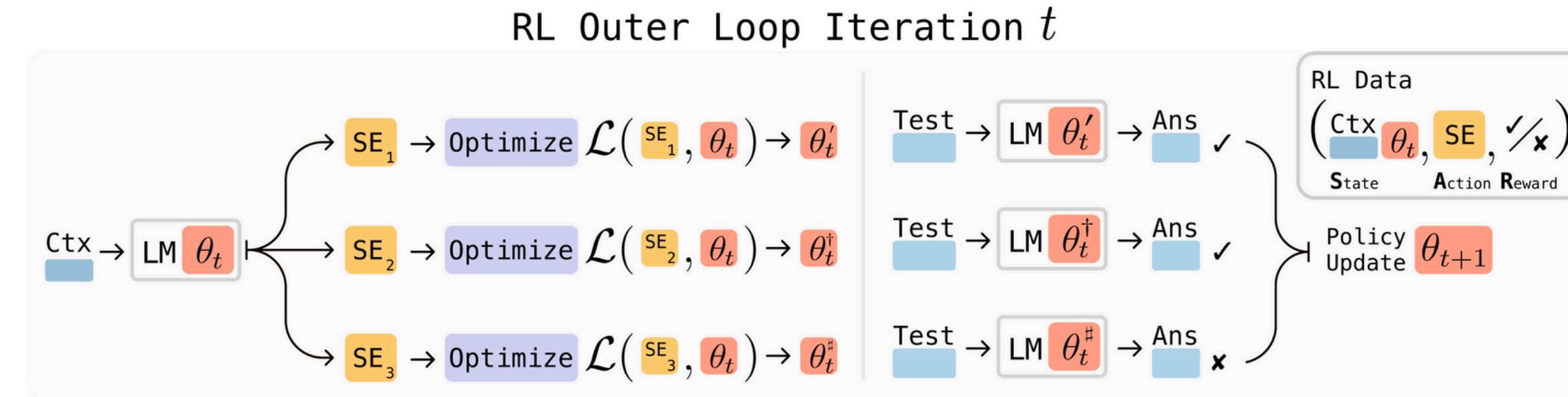
MODELS THAT **WRITE THEIR OWN**  
TRAINING DATA

MODELS THAT **DECIDE HOW** TO  
UPDATE THEIR WEIGHTS

FRAMEWORK FOR **AUTONOMOUS**  
MODEL EVOLUTION



# HOW SEAL WORKS



## 1. INPUT

MODELS RECEIVES CONTEXT

## 4. EVALUATE

TESTS PERFORMANCE

## 2. SELF-EDIT

TRANSFORMS DATA

## 5. REWARD

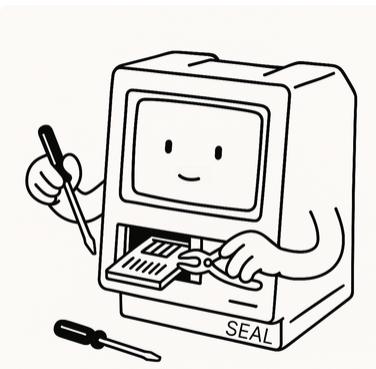
REINFORCES SUCCESS

## 3. FINE-TUNE

UPDATES OWN WEIGHTS

## 6. TRAIN

IMPROVES POLICY



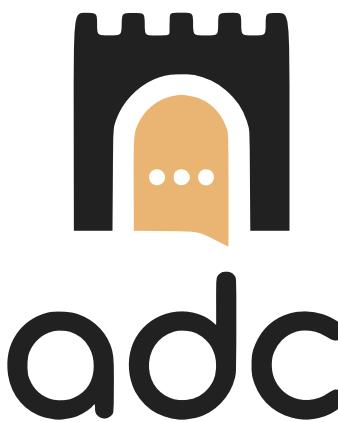
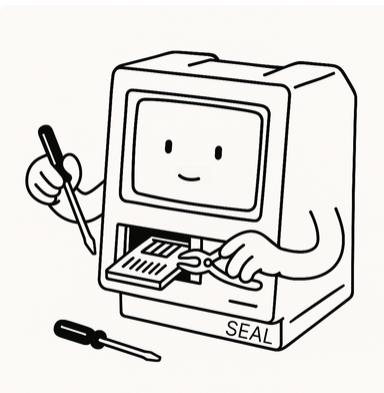
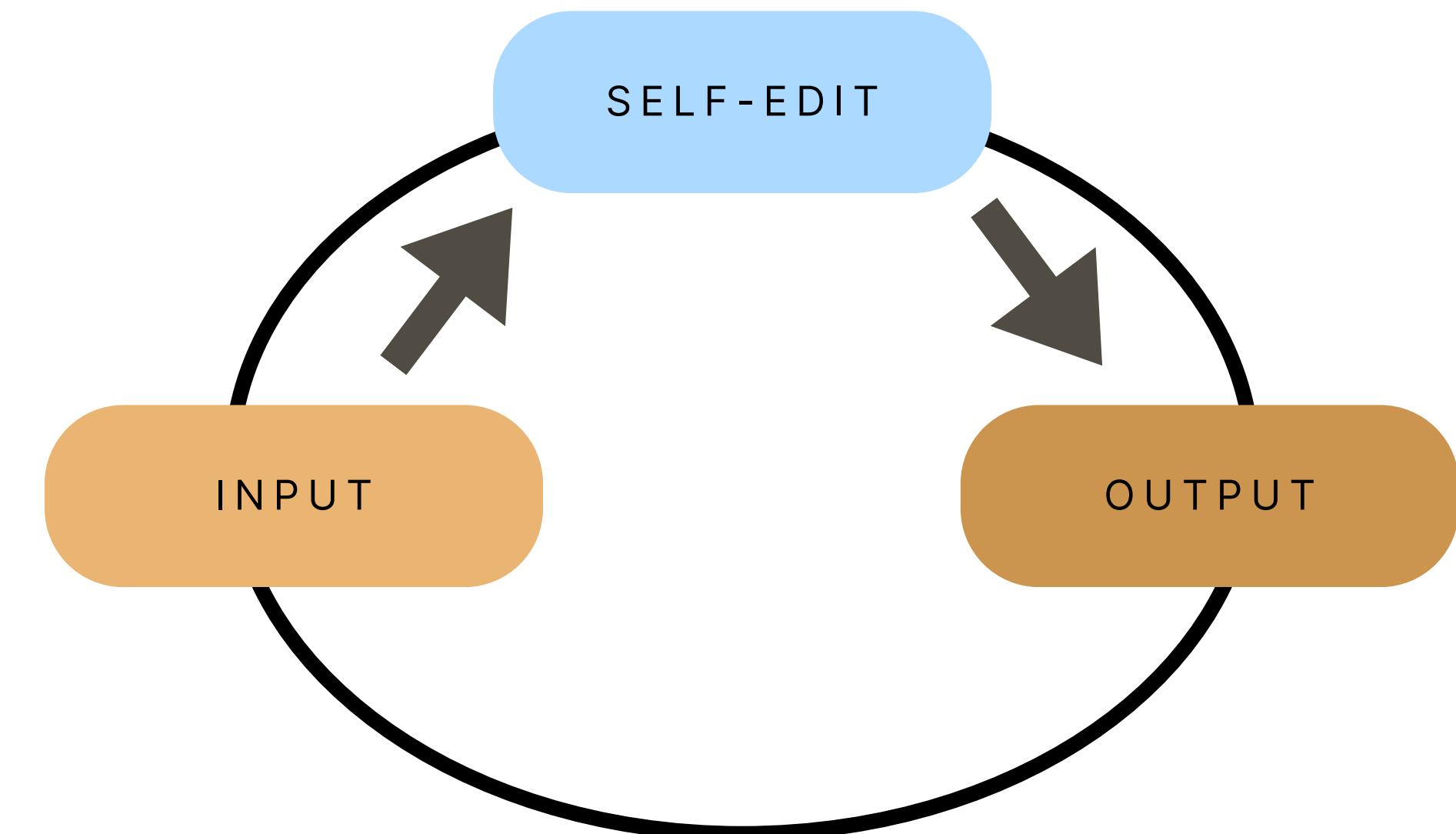
# SELF-EDIT MECHANISM

WHAT IS A SELF-EDIT?

**TRANSFORMATIONS** OF INPUT  
DATA

SELECTION OF  
**HYPERPARAMETERS**

**DIRECTING** THE LEARNING  
PROCESS



# DOMAIN INSTANTIATIONS

## 1. KNOWLEDGE INCORPORATION

### Knowledge Incorporation Setup

#### Passage

**title:** Apollo program  
**context:** But even after NASA reached internal agreement, it was far from smooth sailing...



LM  $\theta_t$

#### Self-Edit

1. The Apollo program faced opposition from Kennedy's science advisor, Jerome Wiesner, who had...

$\theta_t$   
↑

SFT

#### Evaluation

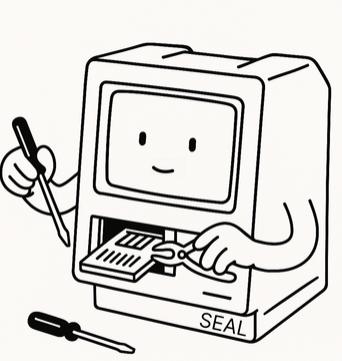
Who was Kennedy's science adviser that opposed manned spacecraft flights?



LM  $\theta'_t$



Jerome Wiesner

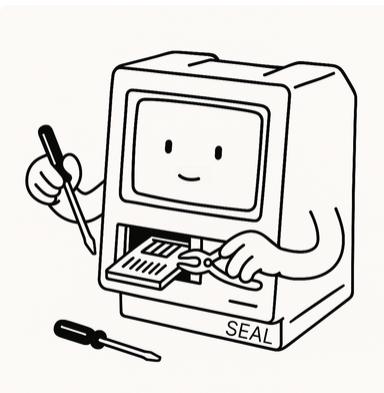
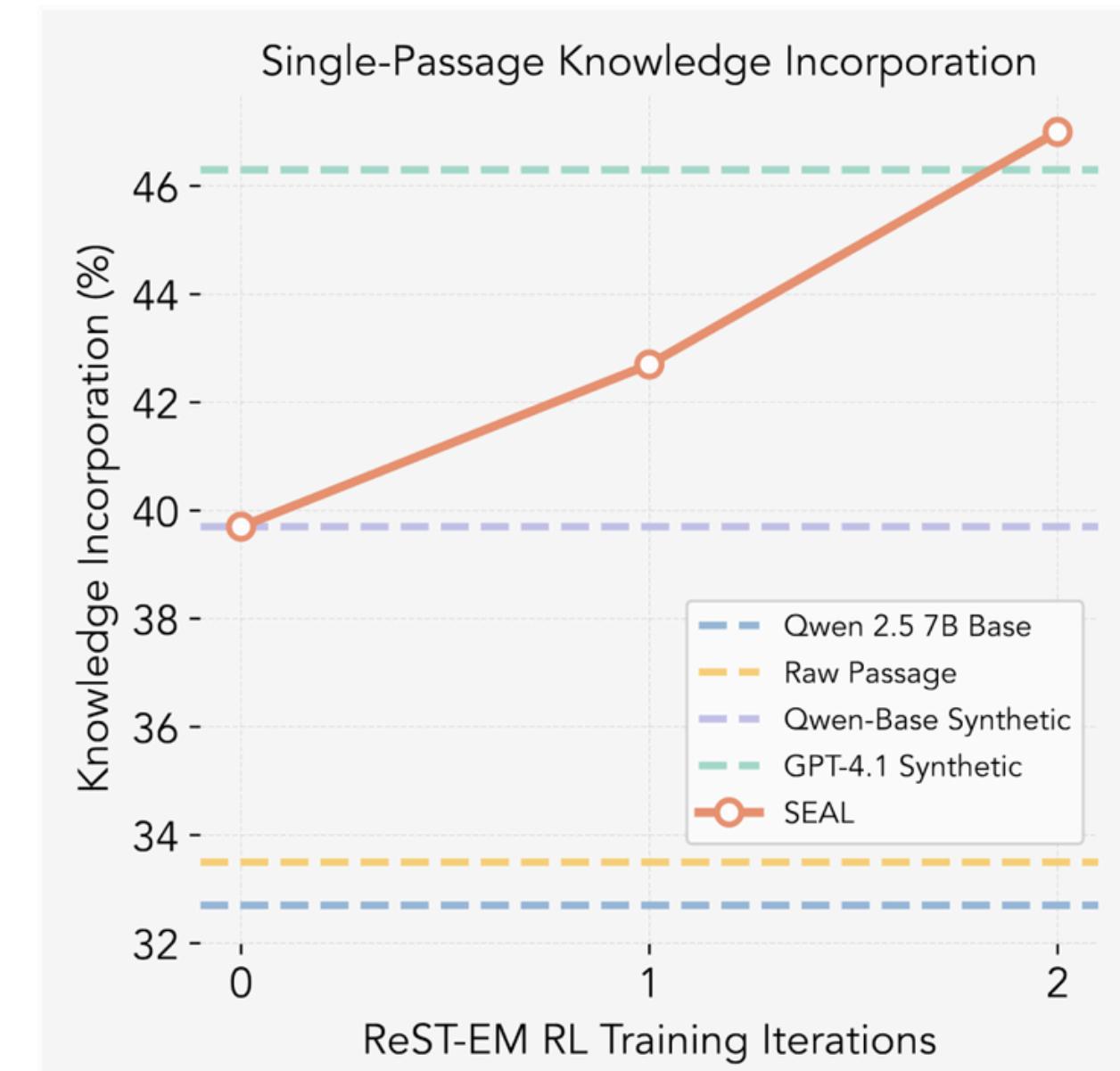


# DOMAIN INSTANTIATIONS

## 1. KNOWLEDGE INCORPORATION

<b>Method</b>	<b>Single Passage (n = 1)</b>	<b>Continued Pretraining (n = 200)</b>
Base model	32.7	32.7
Train on Passage	33.5	32.2
Train on Passage + Synthetic	39.7	41.0
Train on Passage + GPT-4.1 Synthetic	46.3	39.4
<b>SEAL</b>	<b>47.0</b>	<b>43.8</b>

Table 2: Knowledge Incorporation Performance across Passage Settings

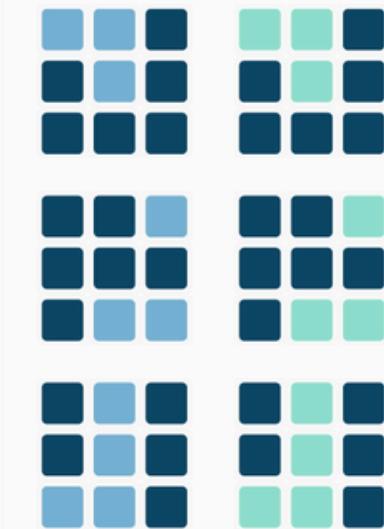


# DOMAIN INSTANTIATIONS

## 2. FEW-SHOT LEARNING

### Few-Shot Setup

Few-Shot Examples

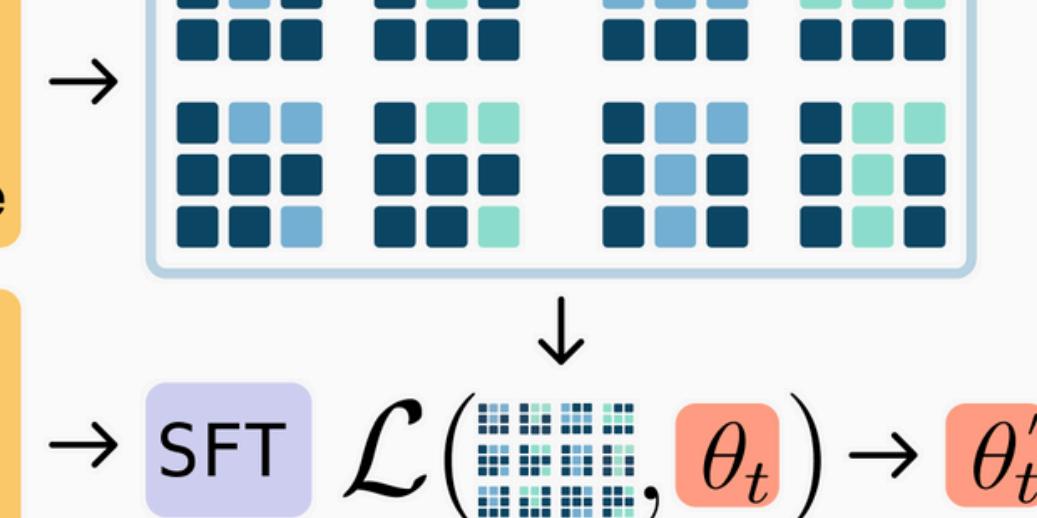


→ LM  $\theta_t$

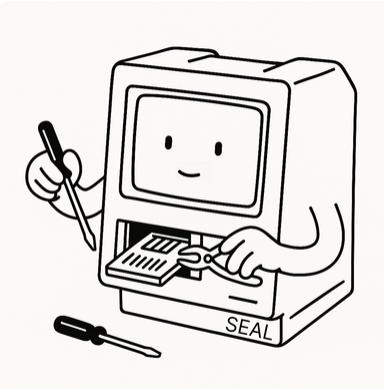
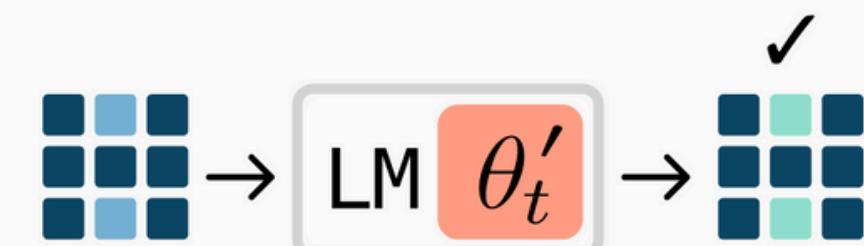
#### Self-Edit (SE)

basic\_augmentations: **true**  
size\_augmentations: **false**  
chain\_augmentations: **false**  
repeat\_augmentations: **false**

strategy: **loss on all tokens**  
learning rate: **1e-05**  
epochs: **3**



#### Evaluation



# DOMAIN INSTANTIATIONS

## 2. FEW-SHOT LEARNING

Method	Success Rate (%)
ICL	0
TTT + Self-Edit (w/o prior RL)	20
SEAL	72.5
Oracle TTT	100

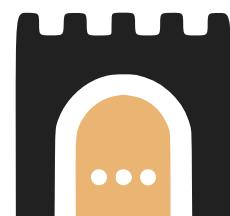
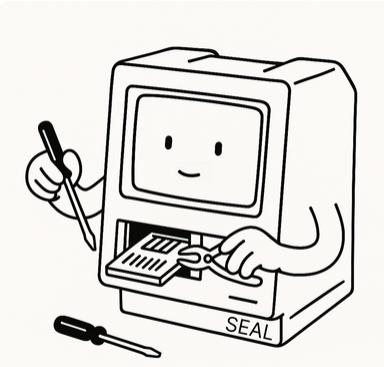
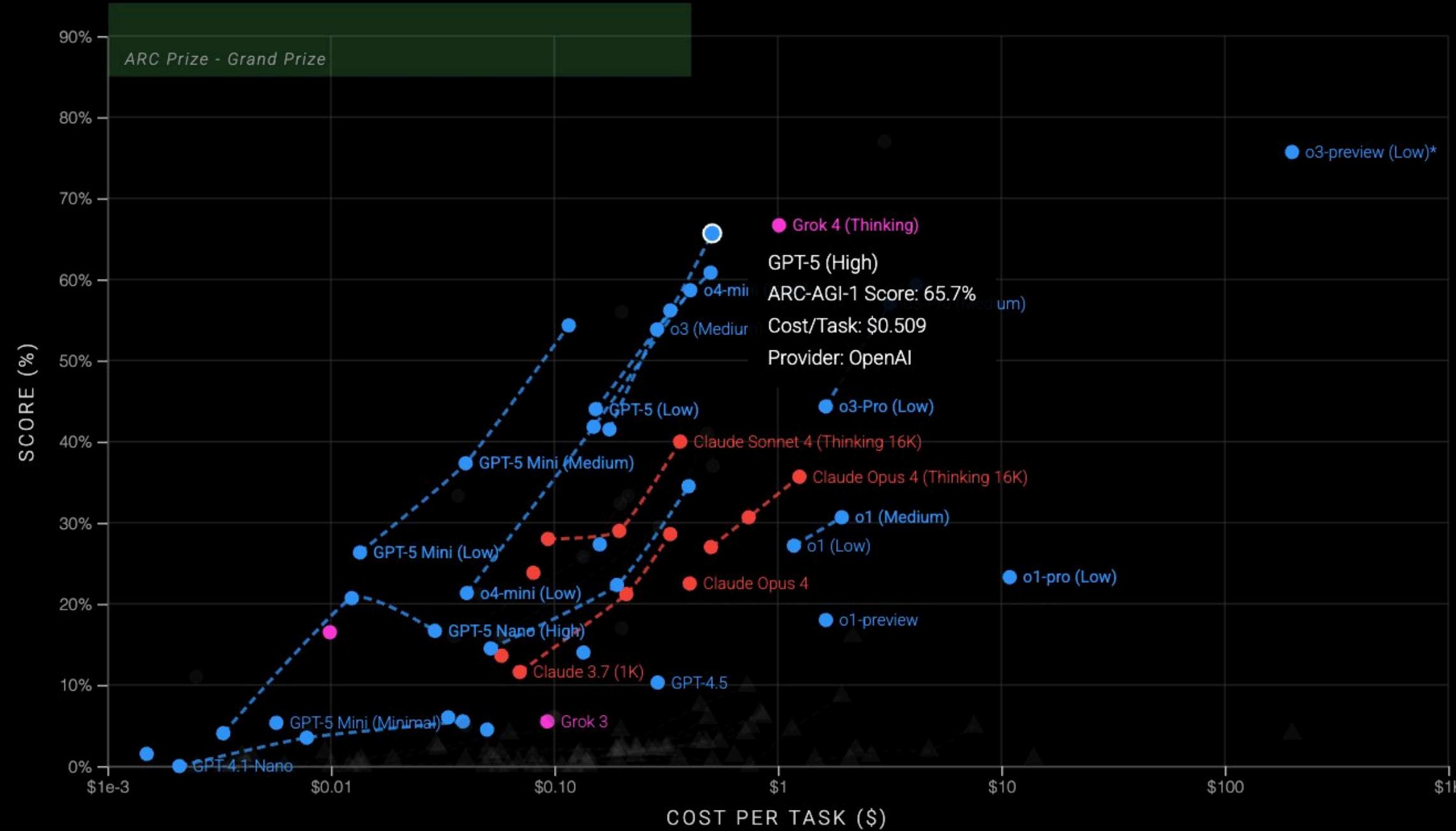
Table 1: Few-shot Abstract Reasoning



# DOMAIN INSTANTIATIONS

## 2. FEW-SHOT LEARNING

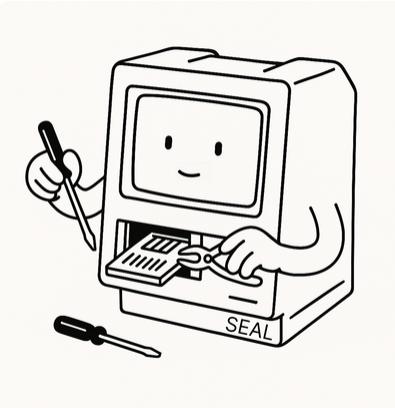
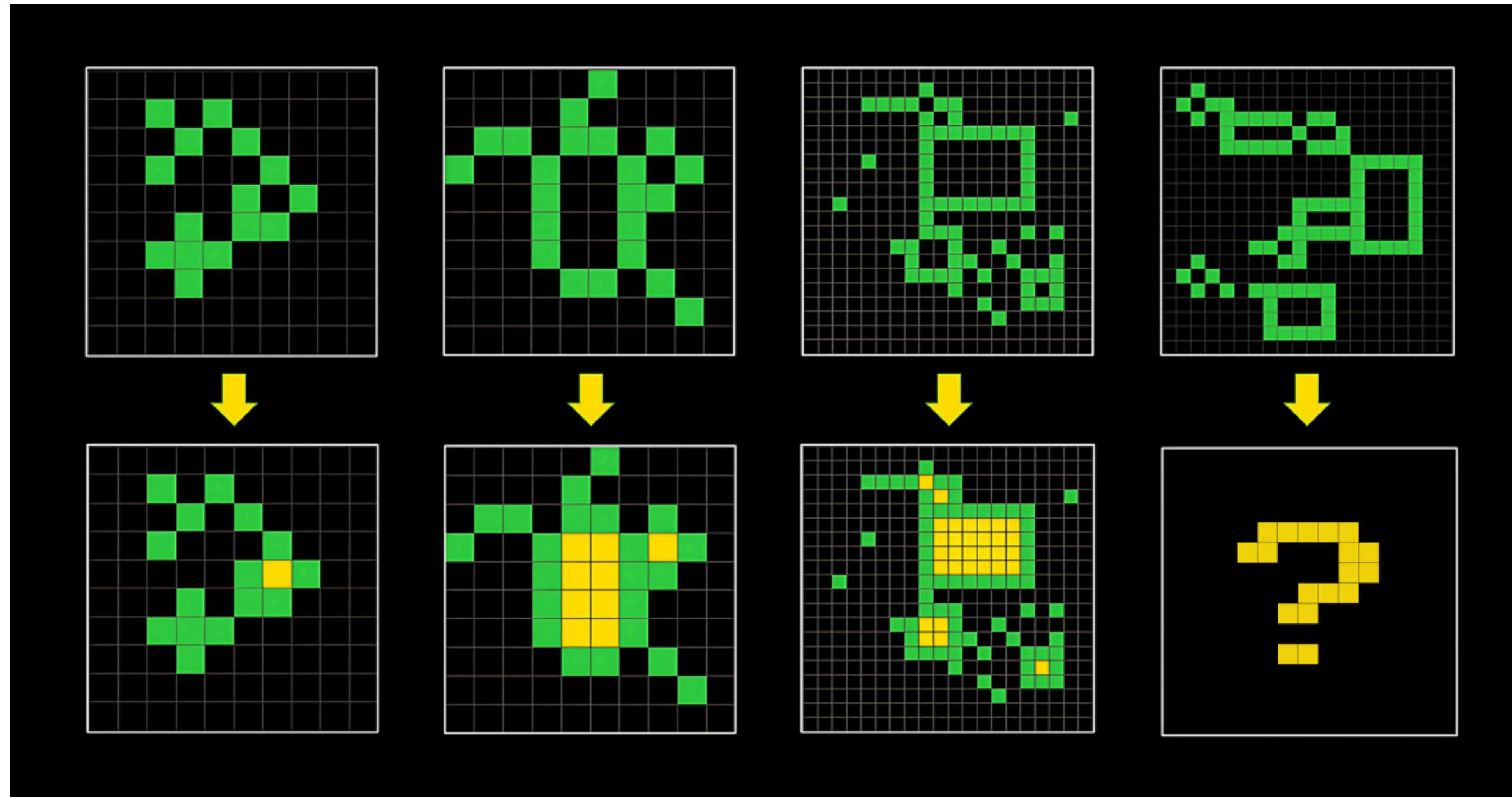
### ARC-AGI-1 LEADERBOARD



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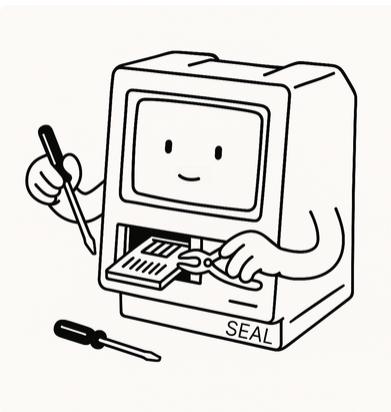
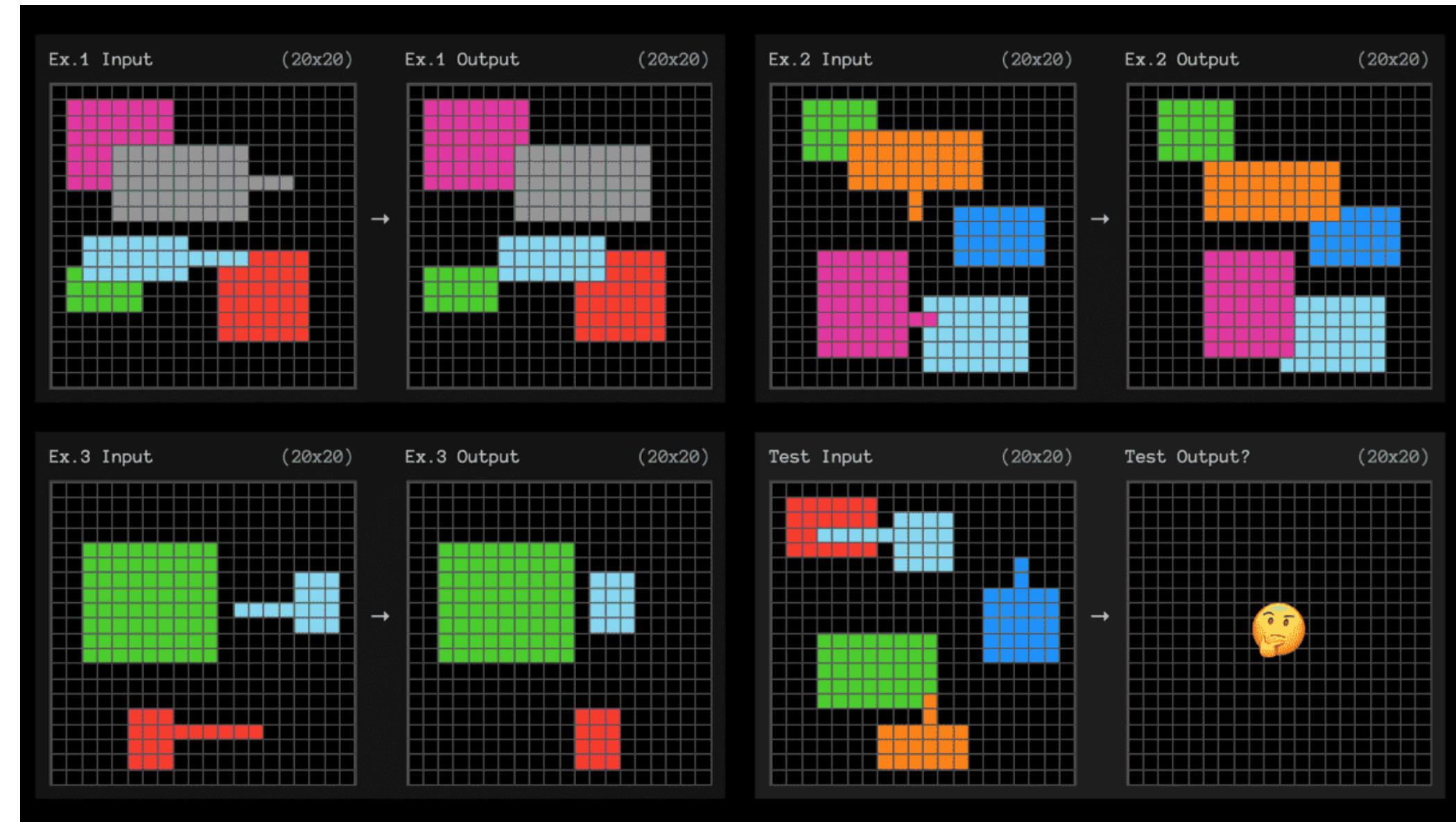
# DOMAIN INSTANTIATIONS

## 2. FEW-SHOT LEARNING



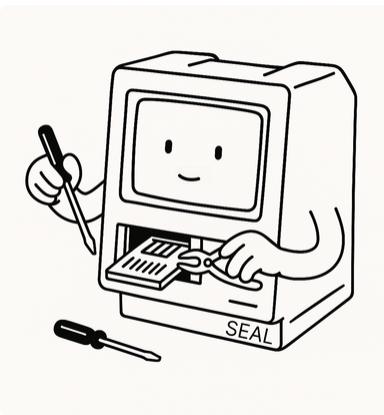
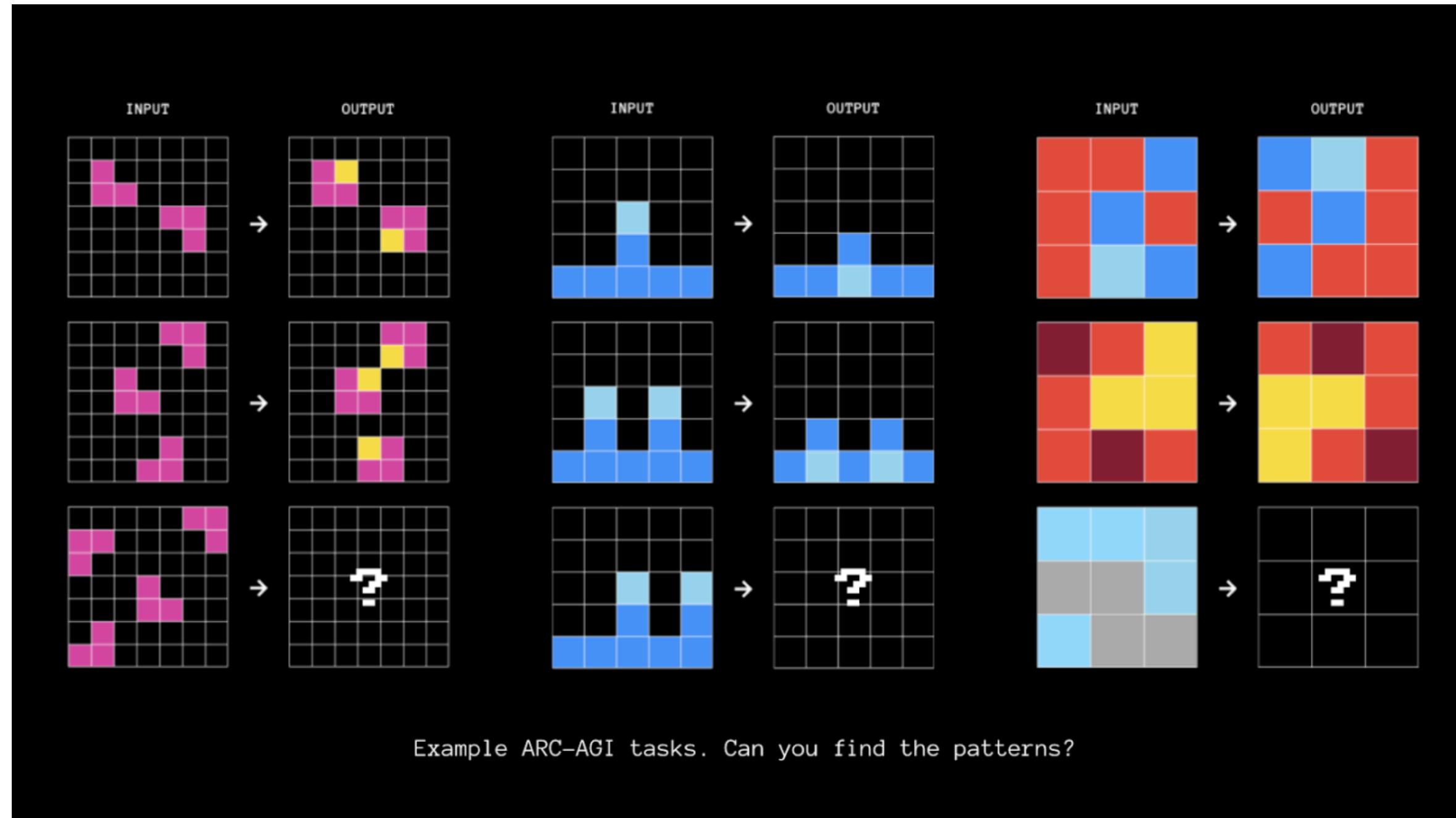
# DOMAIN INSTANTIATIONS

## 2. FEW-SHOT LEARNING



# DOMAIN INSTANTIATIONS

## 2. FEW-SHOT LEARNING

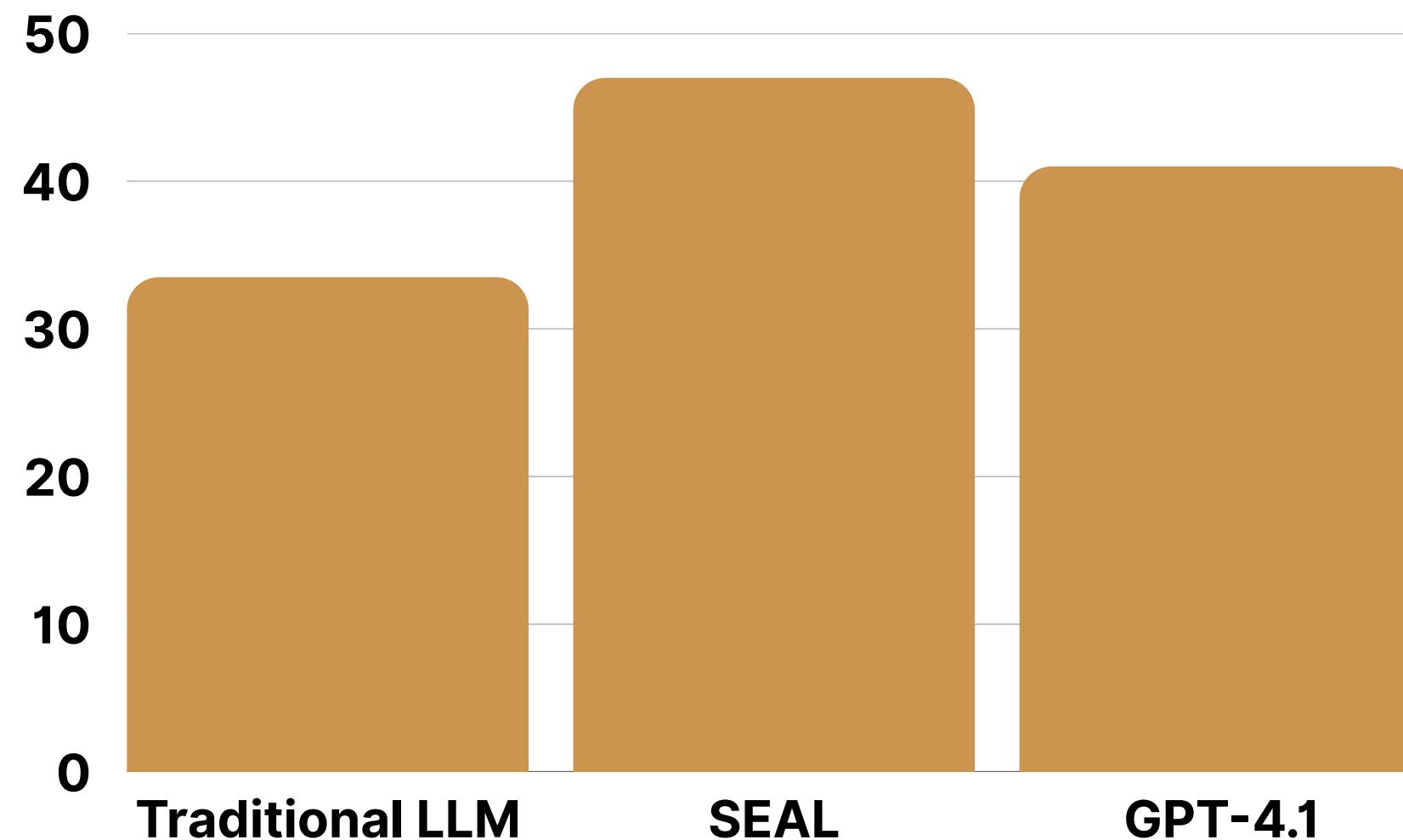


[HTTPS://ARCPRIZE.ORG/PLAY](https://arcprize.org/play)

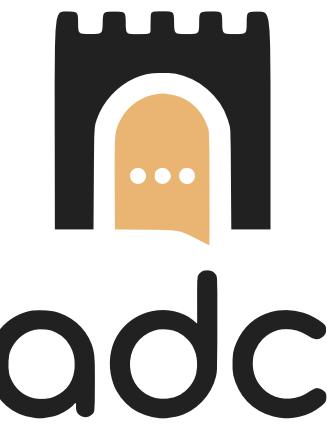
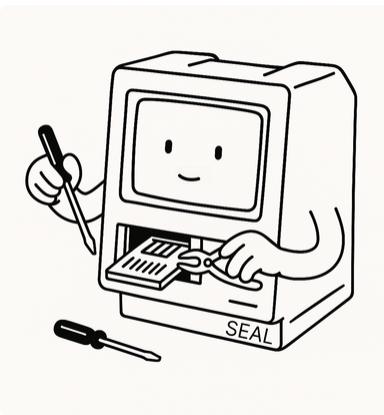
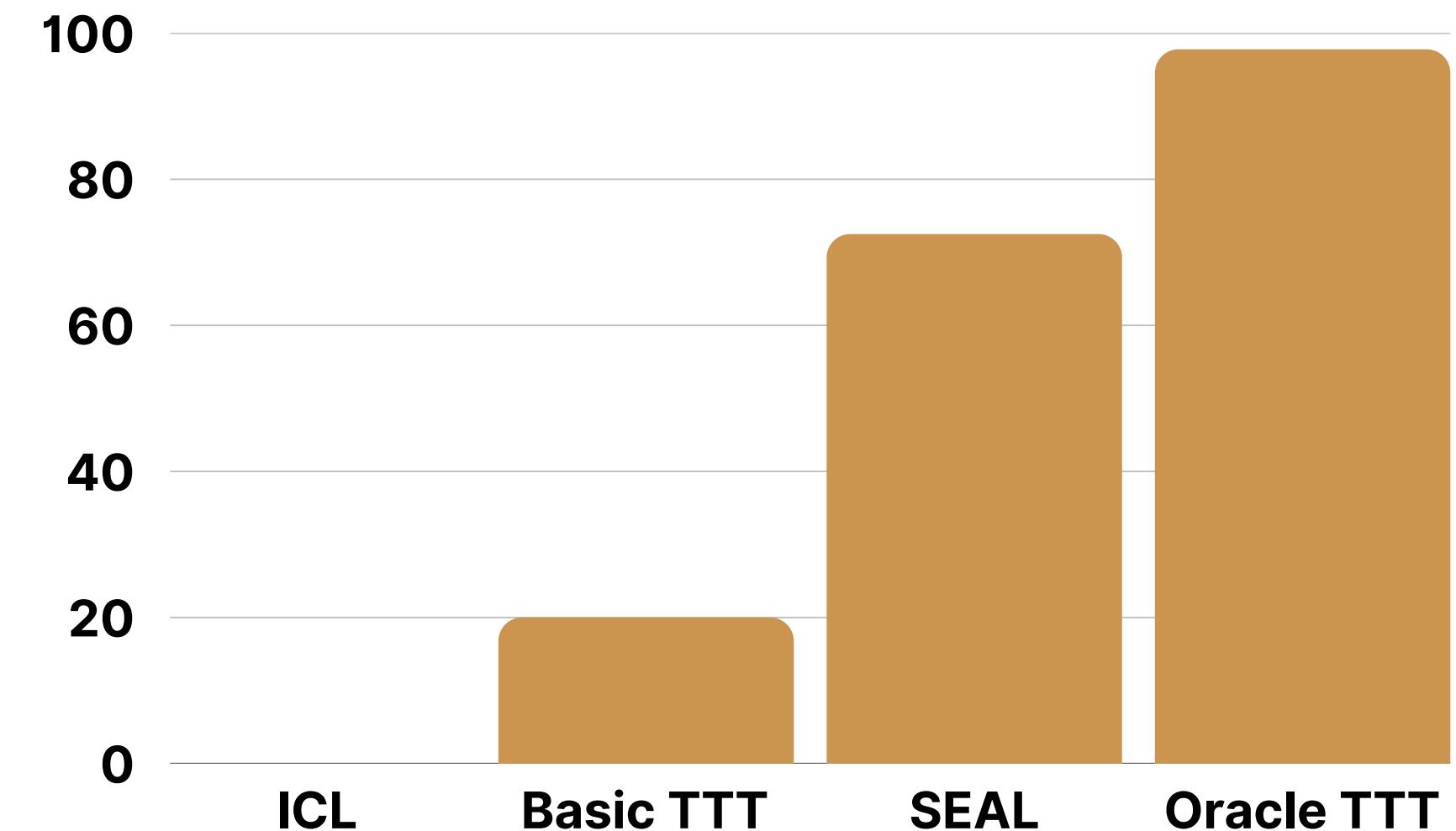


# EXPIRMENTALS RESULTS

KNOWLEDGE INCORPORATION



FEW-SHOT GENERALIZATION



# WHY THIS MATTERS

## ★ BREAKING THE DATA CEILING

MODELS WILL SOON EXHAUST ALL HIGH-  
QUALITY HUMAN TEXT

## ★ SCALING BEYOND HUMANS

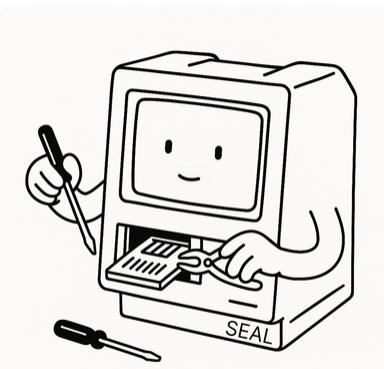
HUMAN-CURATED FINE-TUNING DOES NOT  
SCALE

## ★ ENABLING AGENTIC SYSTEMS

SYSTEMS THAT LIVE AND ACT IN THE WORLD  
MUST LEARN FROM EXPERIENCE

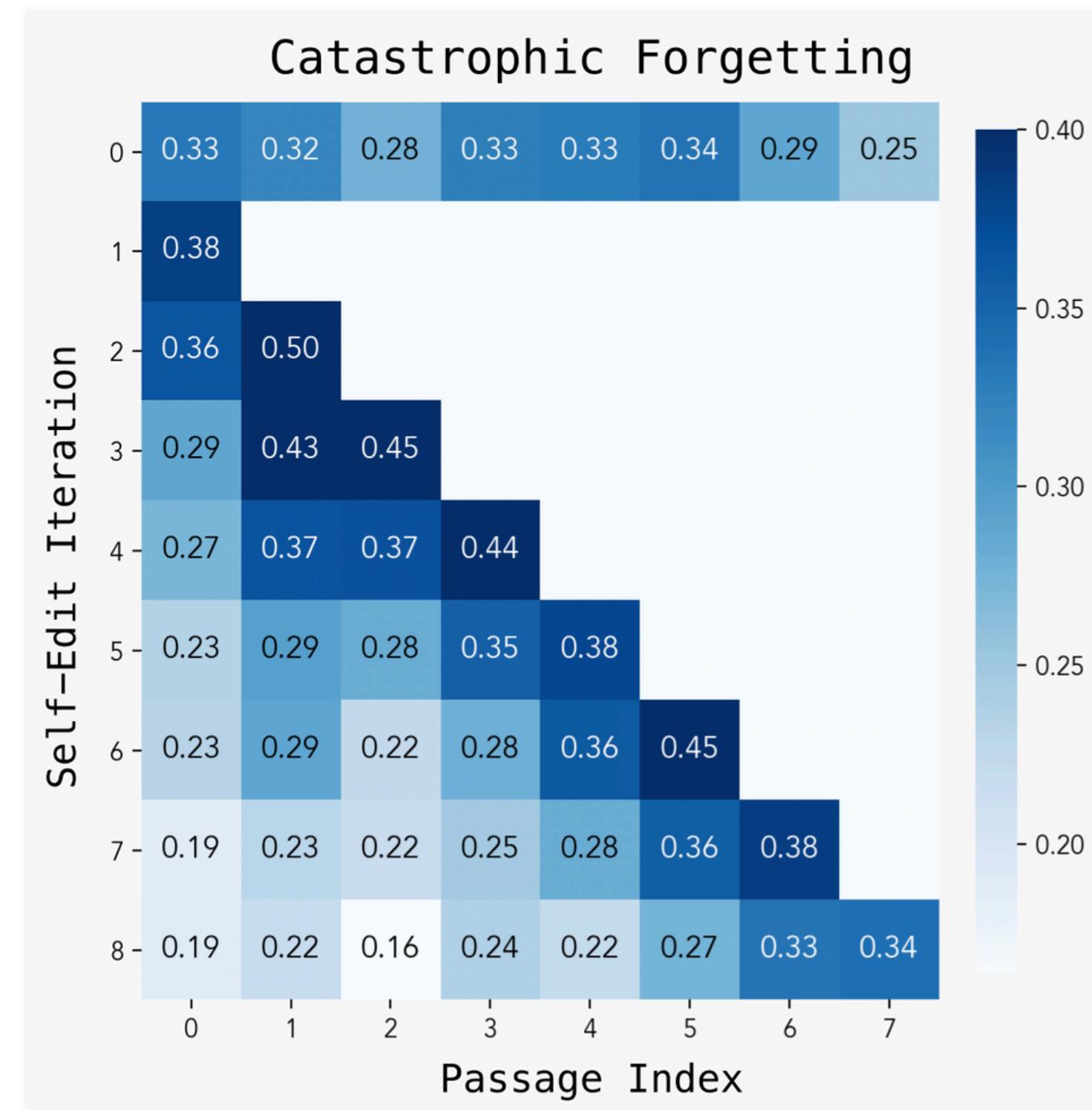
## ★ PATH TO SELF-EVOLVING AI

MODELS THAT DO NOT JUST USE DATA--  
THAY MAKE IT



# LIMITATIONS

## CATASTROPHIC FORGETTING



# FUTURE DIRECTIONS

## ★ CATASTROPHIC FORGETTING

PREVENTING NEW LEARNING FROM  
OVERWRITING OLD KNOWLEDGE

## ★ DOMAIN EXPANSION

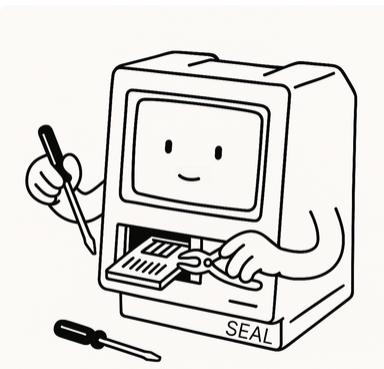
APPLYING SEAL TO MORE DIVERSE TASKS  
AND DOMAINS

## ★ COMPUTATIONAL EFFICIENCY

REDUCING RESOURCE REQUIREMENTS FOR  
SELF-ADAPTATION

## ★ AI DEVELOPMENT

BROADER IMPLICATIONS FOR  
AUTONOMOUS AI SYSTEMS



THANKS!!

