

# **Towards AI-Native Software Engineering (SE 3.0)**

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# How to cite this session?

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# Check this paper for more information about this session

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}
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# Overview of the session

## ❑ Rethinking Software Engineering

- ❑ Software eras
- ❑ Software engineering eras
- ❑ Towards AI-native SE: our vision and technology stack

## ❑ Where are we today?

- ❑ **AI4SE:** A very shallow perspective on the ROI of AI4SE
- ❑ **SE4AI:** Too focused on AI models and prompting instead of AI systems

## ❑ Conclusion



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## ❑ Where are we today?

- ❑ AI4SE: A very shallow perspective on the ROI of AI4SE
- ❑ SE4AI: Too focused on AI models and prompting instead of AI systems

## ❑ Conclusion

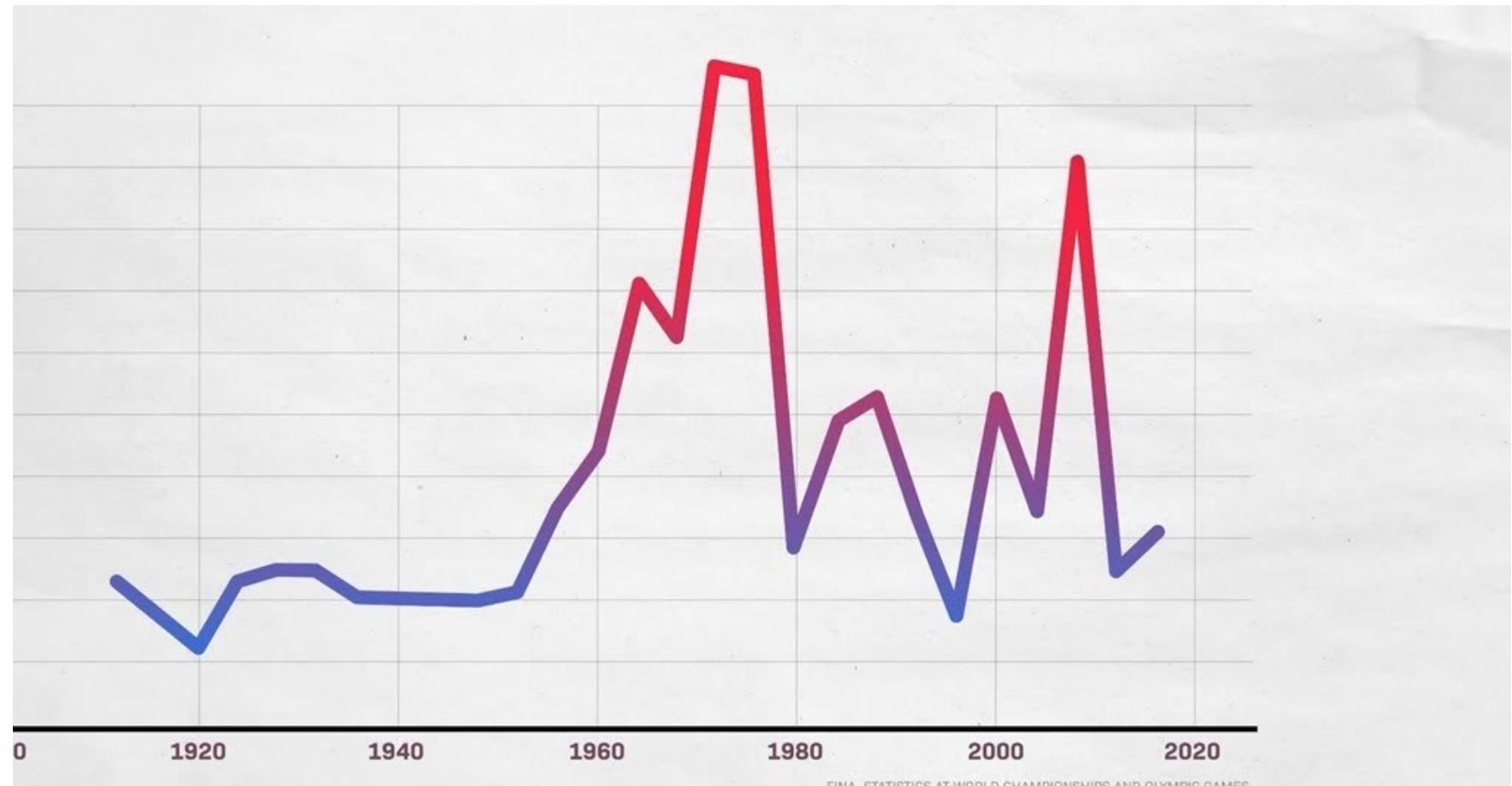


# Avoiding Strategic and Technological Surprises

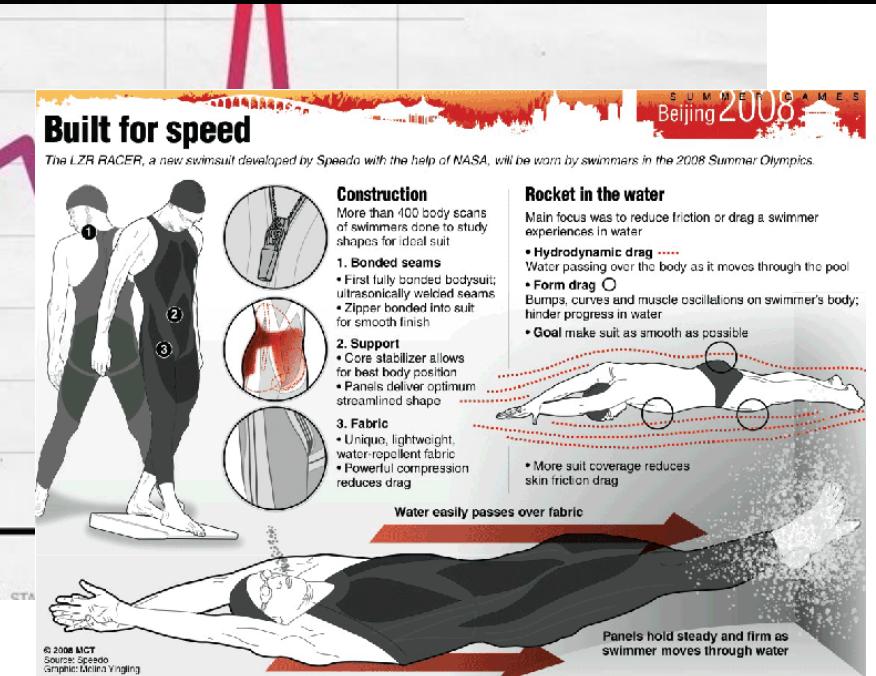
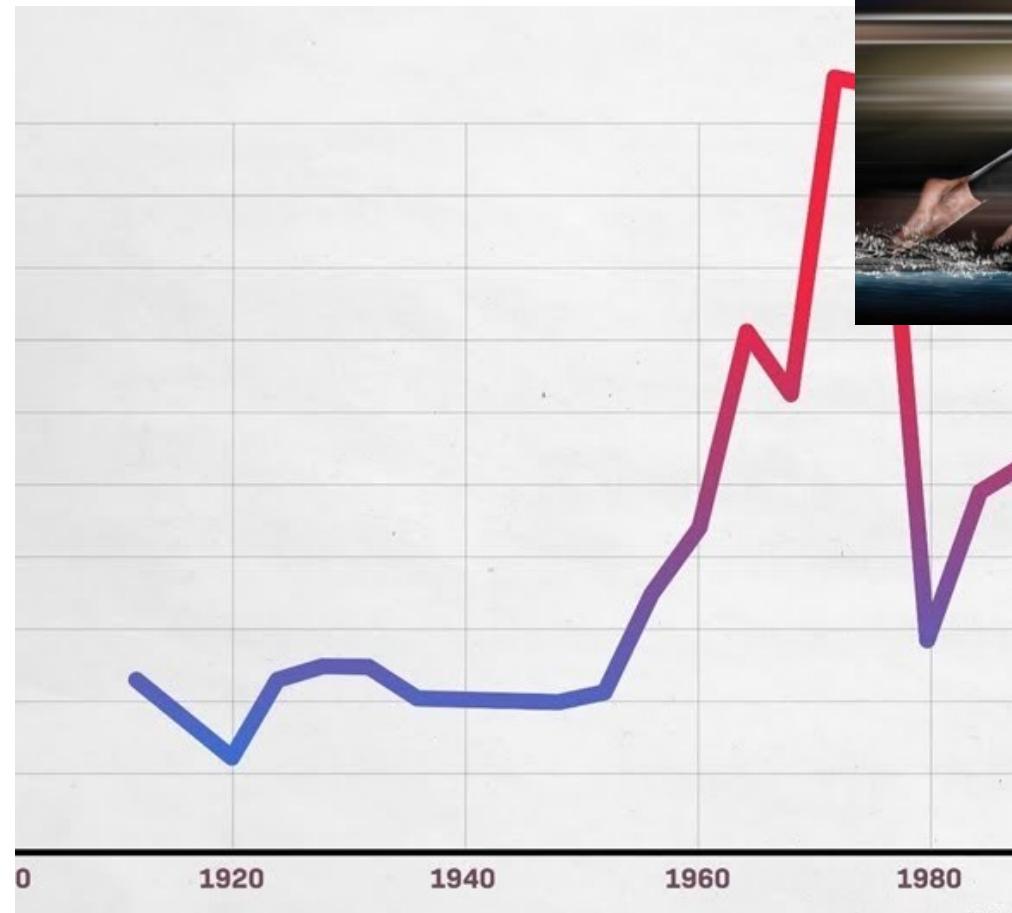
*An innovation engine is needed to undertake, support and direct **high-risk** projects with potential for **game-changing high-return impacts***



**# of  
broken records  
per year  
in Olympics  
& World  
championships  
for swimming**



# # of broken records per year in Olympics & World championships for swimming



# The “Dick Fosbury Flop” in High Jump



**The Straddle**



**Fosbury Flop**

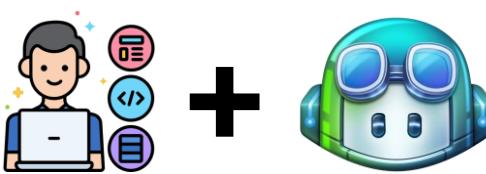
**Mexico 1968 Olympics**

# Alware: Rethinking Software Engineering!



## Software Engineering 1.0

- **Code-first**
- **Tools supporting traditional SE Process activities**
- Powered by **program analysis technologies**

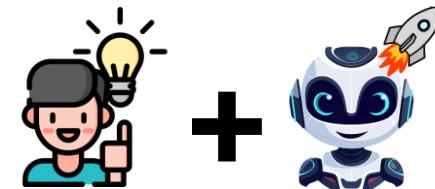


## Software Engineering 2.0

- **Code-first**
- **AI models supporting traditional SE process activities (AI4SE)**
- Powered by **expensive data-driven models** with limited capabilities



*We are mostly here now!*



## Software Engineering 3.0

- **Intent-first, conversation-oriented development**
- **AI-native SE process** maximizing the strengths of human (reqs) & AI (impl)
- Powered by **efficient knowledge-driven models** with advanced reasoning capabilities



# The Brain's last stand



*"We humans are trying to figure out our next move"* Dan Rather, NBC



“A **weak** human player + machine  
+ *better process*

is superior

to a very powerful machine alone,

But **more remarkably** is superior to

a **stronger** human player + machine

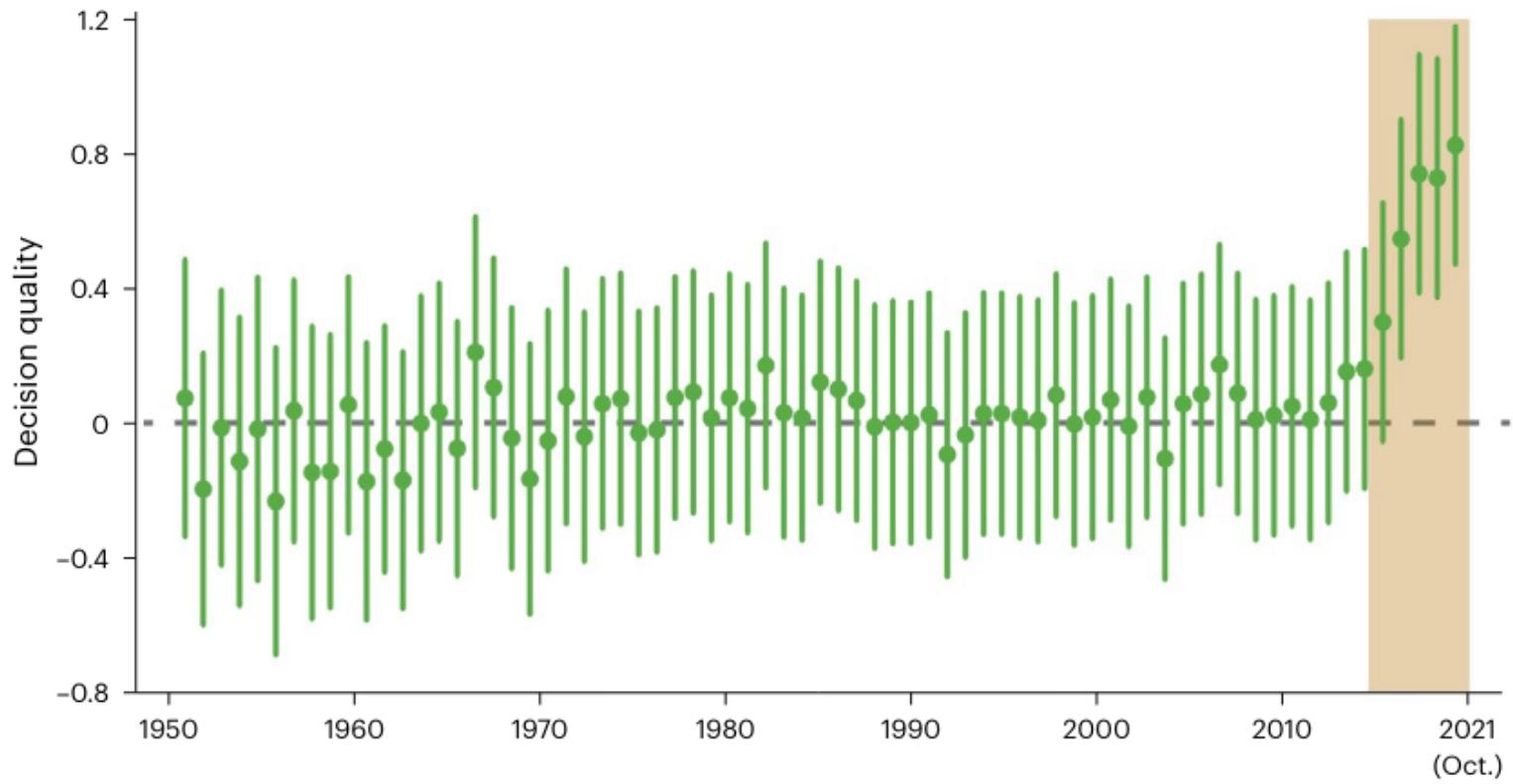
+ *inferior process* ”

*Gary Gasparov*



# AI can make developers better

- Strong teams attract strong candidates, making them stronger and keeping them longer → You AI teammate is a coach that is making you a better developer



Decision quality of professional Go players evaluated through an algorithm that is performing at a superhuman level. Decision quality significantly increased after Sedol was beaten by AlphaGo on 15 March 2016 (shaded area) [Brinkmann 2003]



# What is Software Engineering?

The needed **R&D capabilities+ Programming System** for the *efficient transformation* of **Intent** to *high quality* Software

**Code is just a means to an end!**

Yet today it is treated as the most important aspect, we care about code quality, code health, code automation.... Instead **Intent which is the most important aspect is IGNORED!!**





# Teammate.next

Personalized AI partners

## IDE.next

(Developing, Debugging, Maintaining)  
Intent-First + Conversational

## Compiler.next

Code realization through  
synthesis and search

## Runtime.next

SLA-aware Uni-Cluster Runtime  
with Edge Extension

## FM.next

Curriculum engineered models

We are  
re-thinking the  
Software &  
SE Stacks

*Actually we are also rethinking the programming  
model itself 😊 [observable verifiable and controllable  
multi-agents framework]!*





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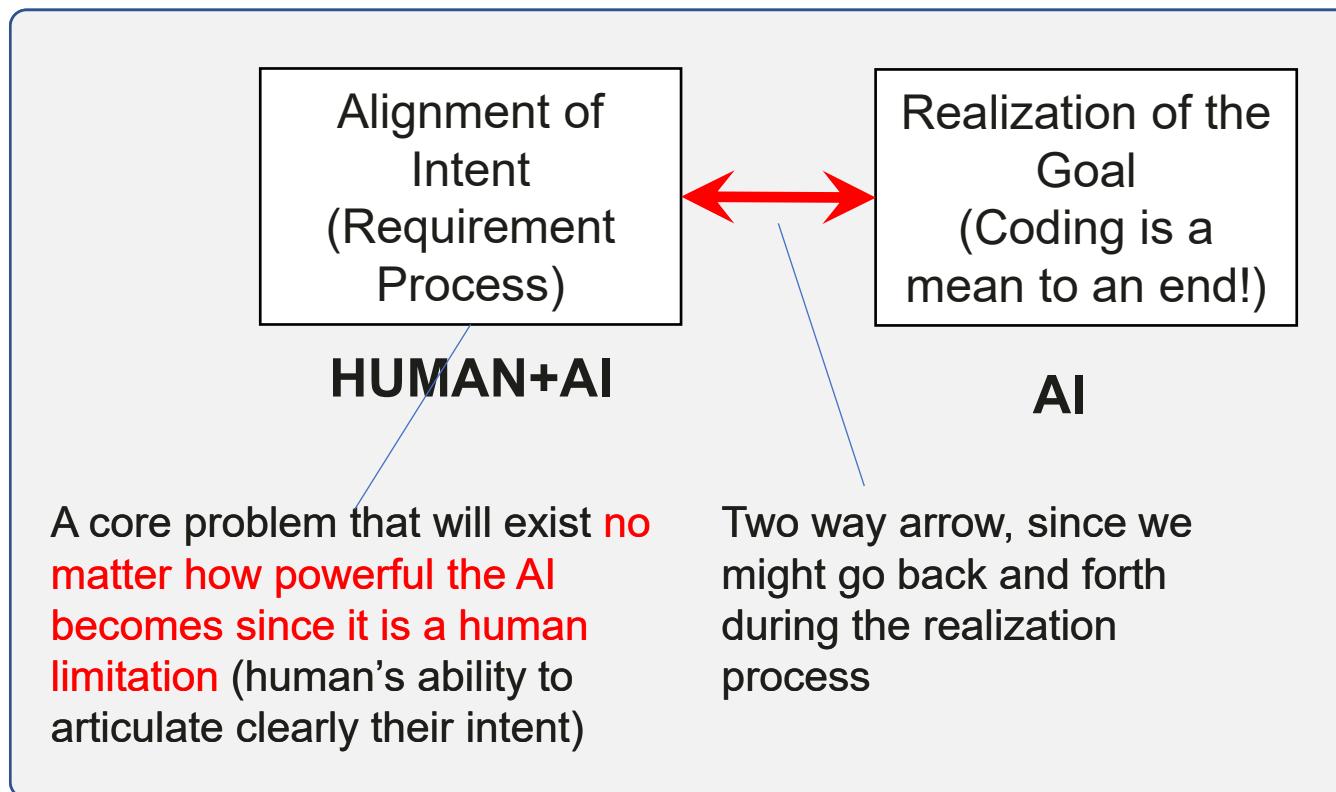
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# AI-Native SE: Intent-Centric instead of Code-Centric SE



## TRADITIONALLY:

1. SE spends great amount of time on Intent alignment as cost to adjust the system realization is too high if we misunderstand the expectations/ requirements.
2. SE is static. It is worried about the realization since new Intents must be integrated into the old static view of the system

## OUR VISION:

1. AI is great at automation, Human is not great at expressing their needs/requirements  
→ AI works with Human back and forth to align expectations
2. The AI-native realization process can run at hyper-speed + AI is much smarter than the human requirement analyst  
→ AI can see much further and find confusions much faster then go back to re-align with human.

## CORE CHALLENGES:

1. Speed up the alignment otherwise human will be frustrated if they must state the obvious or repeat themselves!
2. Make sure realization is grounded on “best-practices”



# Conversational-Oriented Programming (COP)

- The conversations are the intellectual property and not the code
- The conversations should be archived as they are even more important than the code itself! **Code is the new binary!**
- The conversations capture intents, goals and requirements
- We can always *re-realize the code* by converting such conversations into code again as FM/LLMs get better
- Yet our SE tooling today doesn't account for this, nor do they enable ***deep conversations:***
  - ***Multi-way AI conversations***
  - ***Conversations with delay response (aka not interactive ones)***



# Conversational-Oriented-Programming: The next hop in programming and IDEs



## Classical Programming Editor

- **Code-first**
- **Logic focused**



## Computational/AI Programming Editor

- **Data-first**
- **Output focused**



## AI + Human Co-Programming Editor

- **Chat-first, with Agents instead of plugins**
- **Mental-model/Intent focused**



# Intent Alignment Using “sticky” Theory-of-Mind Bi-directional technology

**Technology:** Communicate with people for multiple rounds of conversations, and properly ask and clarify specific requirements and associated contexts (such as constraints and restrictions).

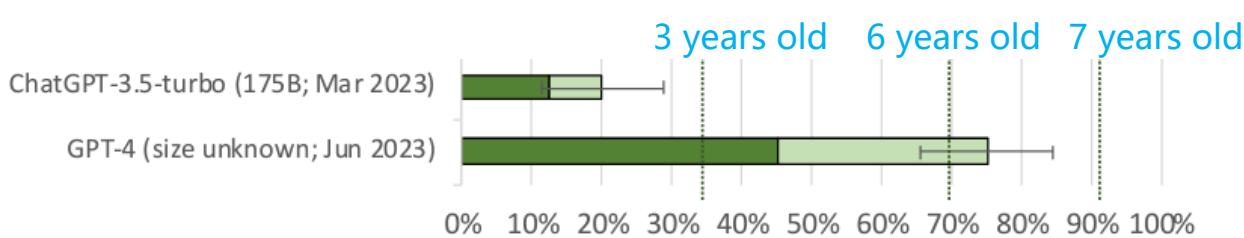


## Theory of Mind

**Challenge 1: Balance over-questioning with under-questioning.** An agent must be able to establish the theory of mind of the person with whom it interacts, that is, to understand the other person's way of thinking and starting point.

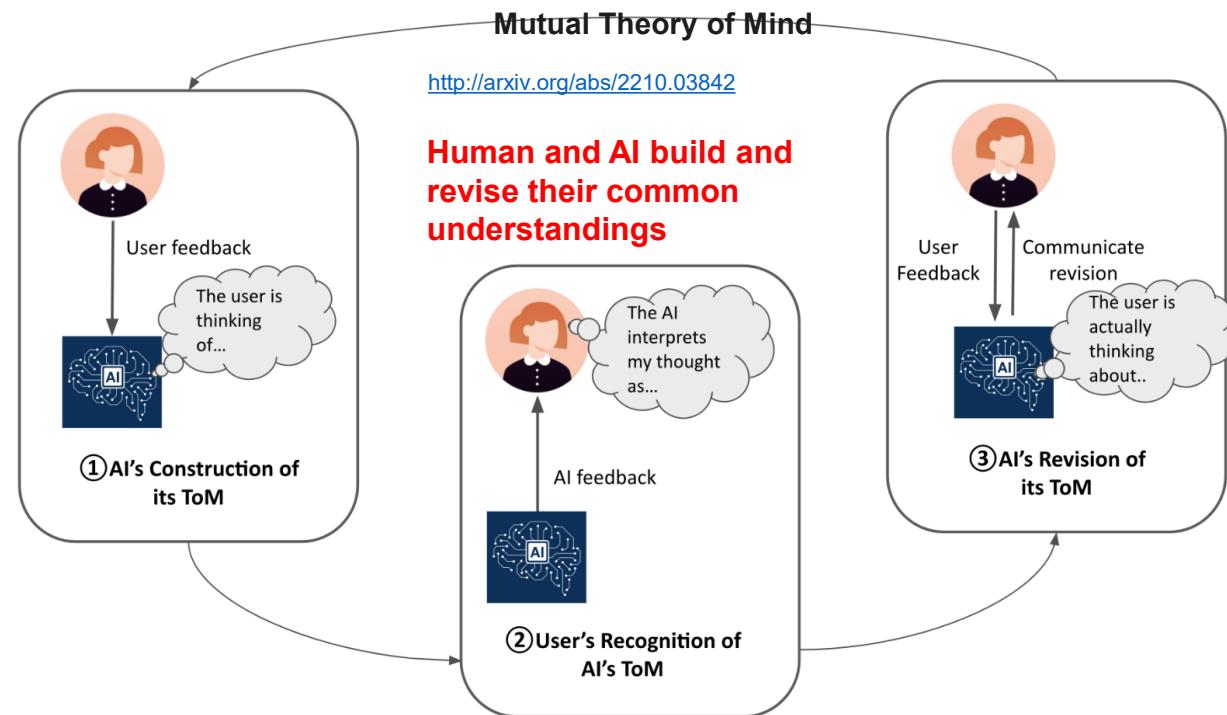
**Challenge 2: ToM must be sticky over interactions yet adjustable to the specific context**

For example, when a supervisor describes a task to a senior member of the team, the wording and level of detail are different than when describing a task to a new employee and varies over time!



### Feasibility Analysis: Large Model Theory of Mind Assessment

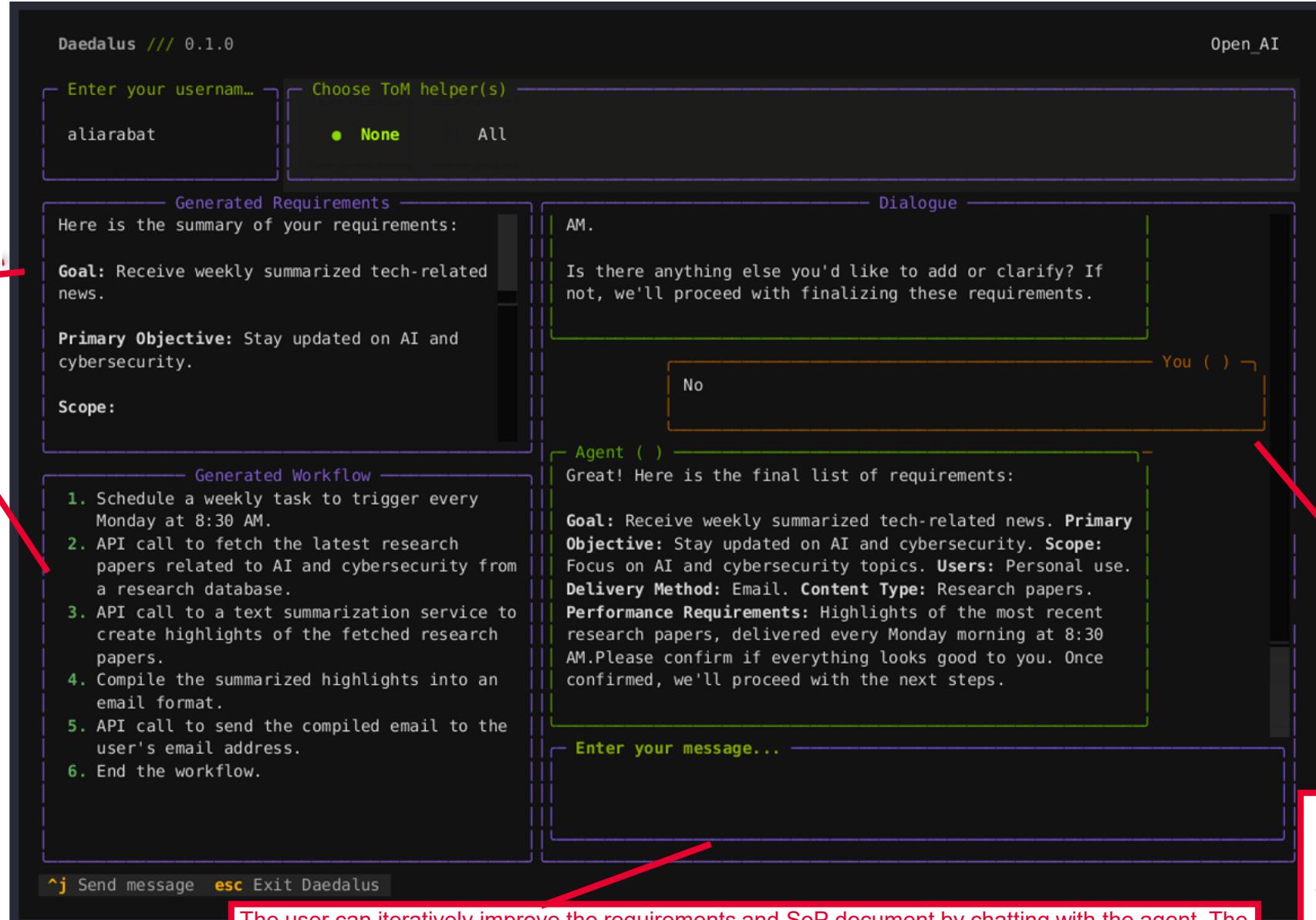
GPT-4 emerges from 0-shot to 6 years of age, feasible and has room for improvement  
(Stanford 2024.2)



Leverage linguistic clues from users' questions. (e.g. readability, emotion, richness of wording, adaptability to agent answers, etc.) to understand the user's perception of the agent. (anthropomorphic, intelligent, favorable, etc.).

<https://dl.acm.org/doi/10.1145/3411764.3445645>





# Conversation-Oriented Programming IDE Demo

(Powered by Theory-of-Mind Intent-Alignment Technology)



```
ali@LAPTOP-C8700QE7:~/projects/daedalus$
```

The agent UI displays a draft version of requirements and SoP as soon as it has sufficient information to do so, in order to get feedback.

*Support for Cognition Debugging Coming in 2025!  
(Resilient to Observer Effect)*

Conversation history helps both the human and GA Agent to keep track of context and identify if something is missing

The user can iteratively improve the requirements and SoP document by chatting with the agent. The user doesn't have to explicitly say their request is for SoP or requirements refinement.

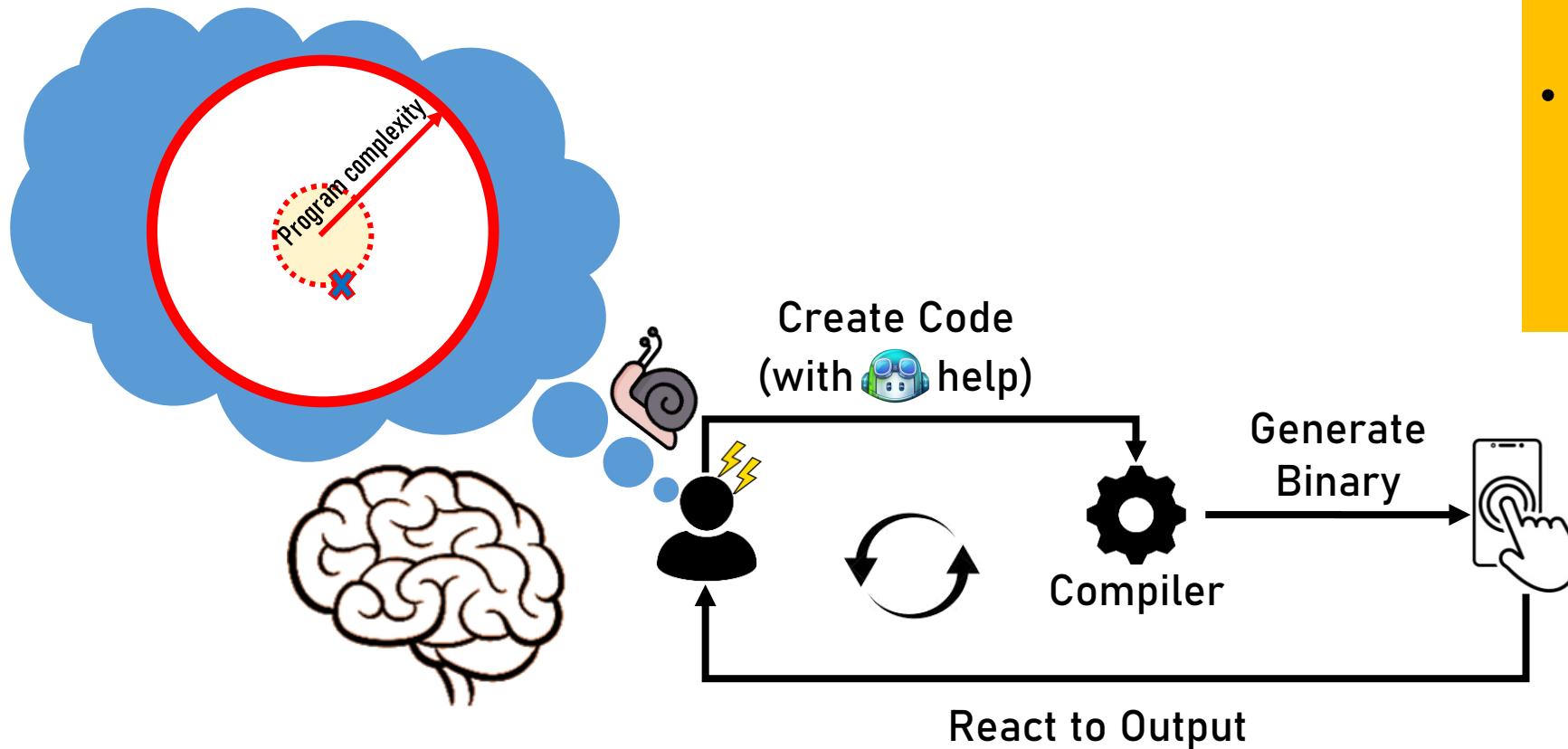
# Conversation-Oriented Programming IDE Demo

## (Powered by Theory-of-Mind Intent-Alignment Technology)



# Programming 2.0 [AI Assisted]

## (Write Code with AI help then Compile)

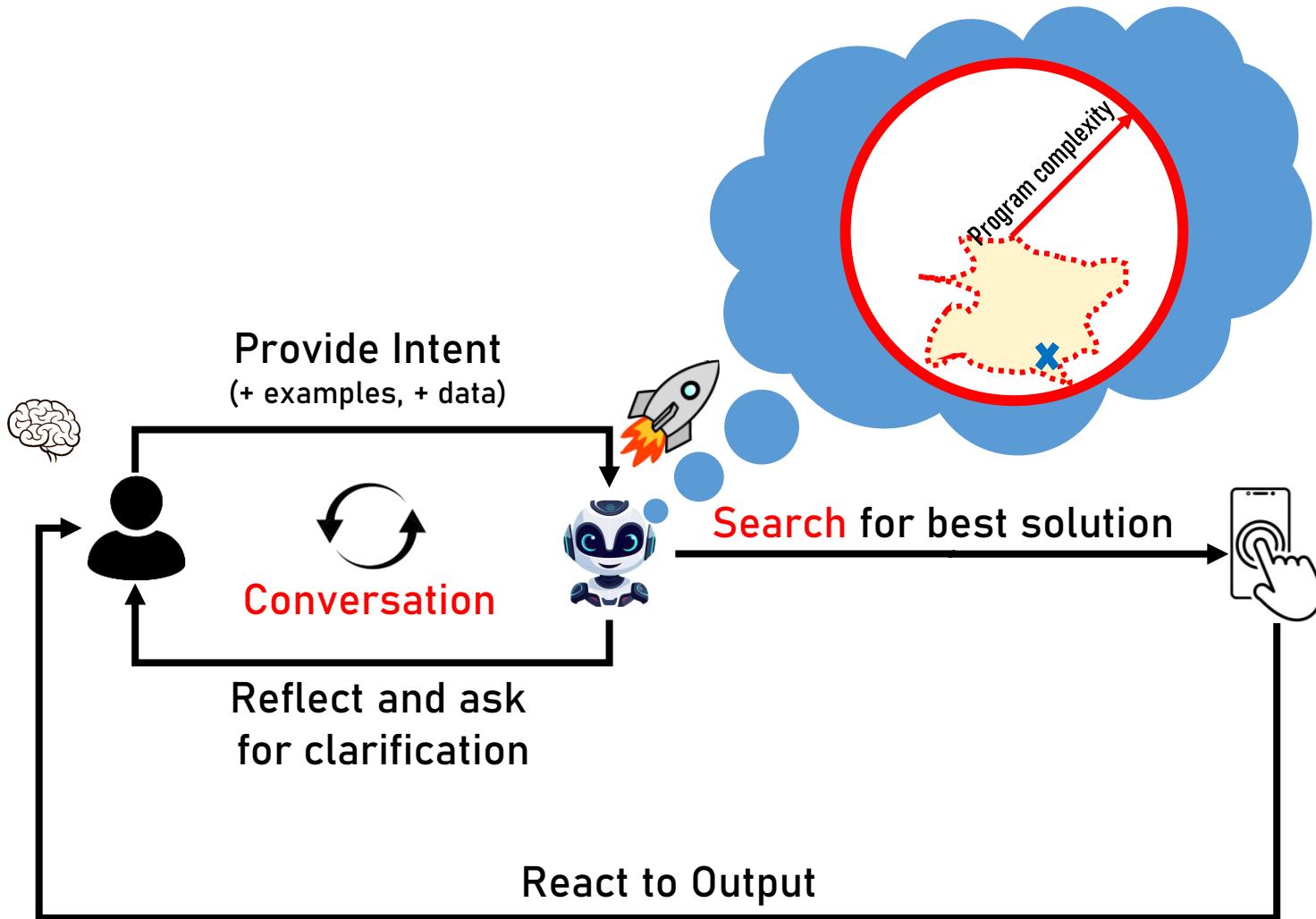


- Human drives the code creation process loop
- The code complexity is limited by human's ability to *express and maintain* a complex problem in code



# Programming 3.0 [AI-Native]

## (Define Search Space, Give Data, AI Searches to create code)



- Human and AI align on goals
- AI drives the code creation loop
- The code complexity is unlimited as the AI synthesizer searches for the “software solution” that maximizes a fitness function (aka Human-AI aligned goals).
- Realization done using Alware or Codeware
- The code creation process can be re-initiated at any time as long as we “archive” the human and AI conversations





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# Fusion (FMware runtime) enables e2e high efficiency SLA-aware serving of FM\LLMware (30% improvement in SLA and latency over default Ray Serve)

**ASIS:** Existing model serving systems

Model centric

Rely on infra for no-context elasticity

No intentions for scheduling



**TOBE:** SLA-aware FMware workflow Serving System (Fusion)

e2e perf. optimization

Routing based on priorities

Allocation based on intelligent predictions

**Core Capabilities:** 2-layer scheduling

Request Router

Determines the model replica to which the current model request is routed.

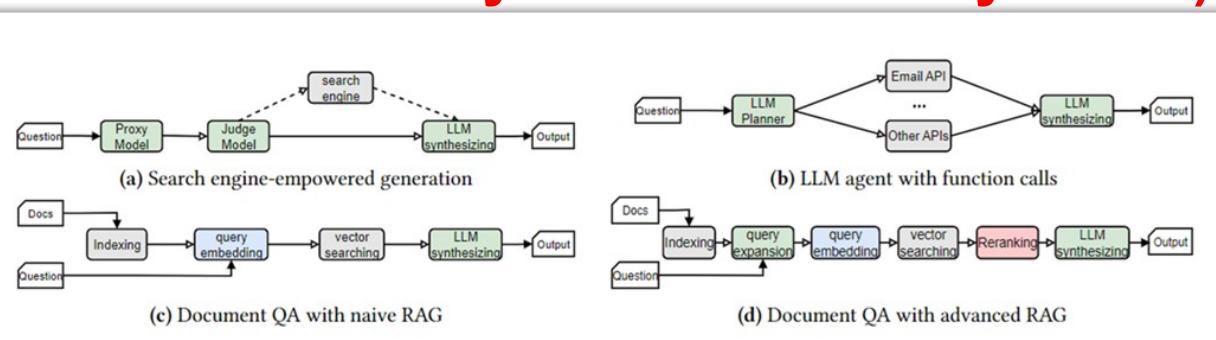


SOTA model acceleration engine

Accelerate model inference

Resource Provisioner

Decide how many replicas each model type should have



## Workflow-Level Expression Model

Workflow A

Model hot Deployment

Workflow B

Profile Metadata

Workflow C

Customized Model Registration

Replica Router

Runtime Metric Collectors

Resource Provisioner

Ray Cluster

Node 1

vllm  
(Model A  
Replica 1)

npu:0 npu:1

vllm  
(Model A  
Replica 2)

npu:2 npu:3

vllm  
(Model B  
Replica 1)

npu:4 npu:6  
npu:5 npu:7

Node N

vllm  
(Model B  
Replica 2)

npu:0 npu:2  
npu:1 npu:3

vllm  
(Model C  
Replica 1)

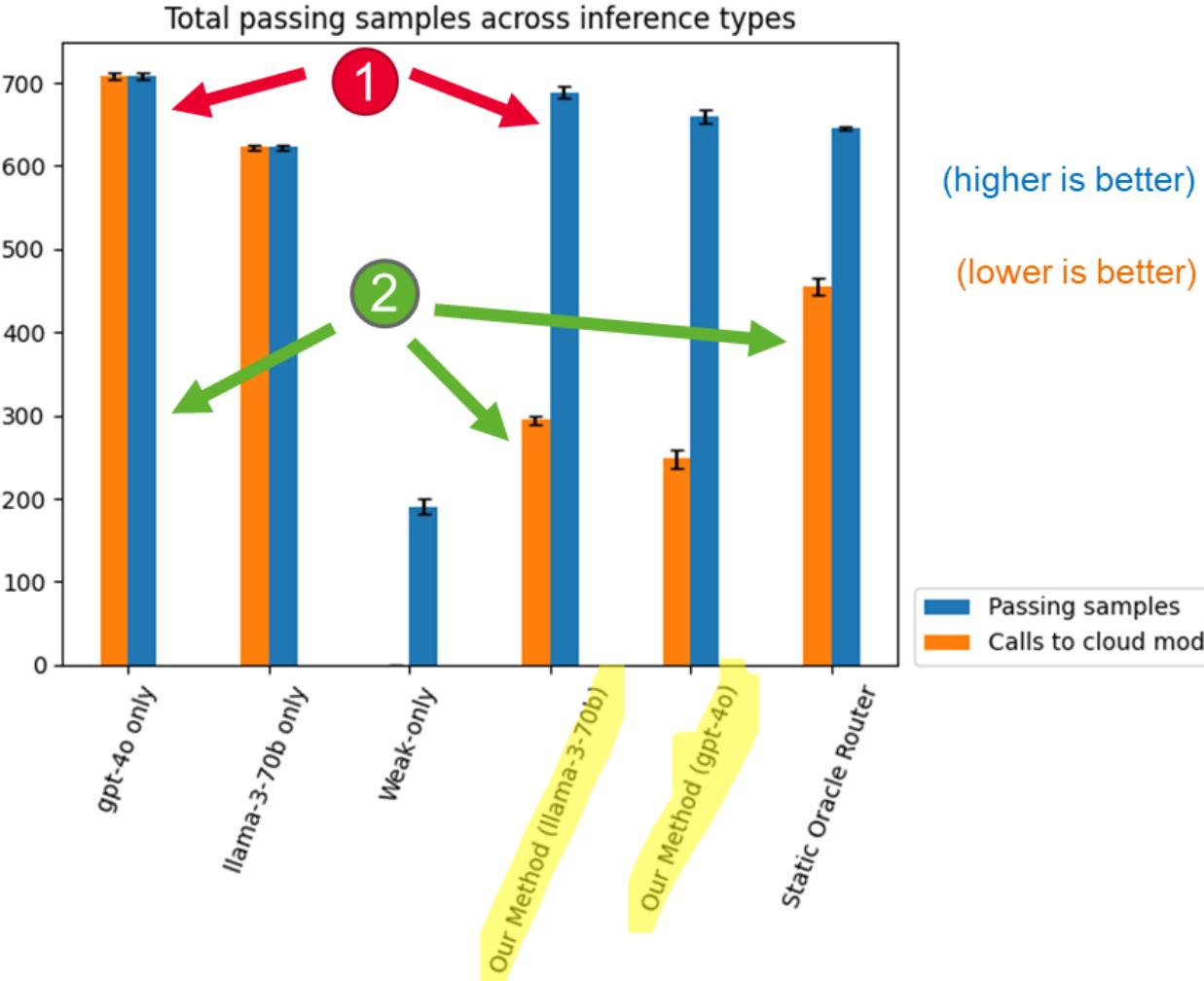
npu:4 npu:5

vllm  
(Model C  
Replica 2)

npu:6 npu:7



# Layered Personalization XPU



- ① Shows *nearly identical* model capability as the *cloud model* (**~96% correctly solved tasks**), and *solves more samples* than *static routing* by **~1-2%**
- ② Makes **~58% less** use of cloud model compared to *cloud model-only inference*, and **~34% less** compared to *static routing*



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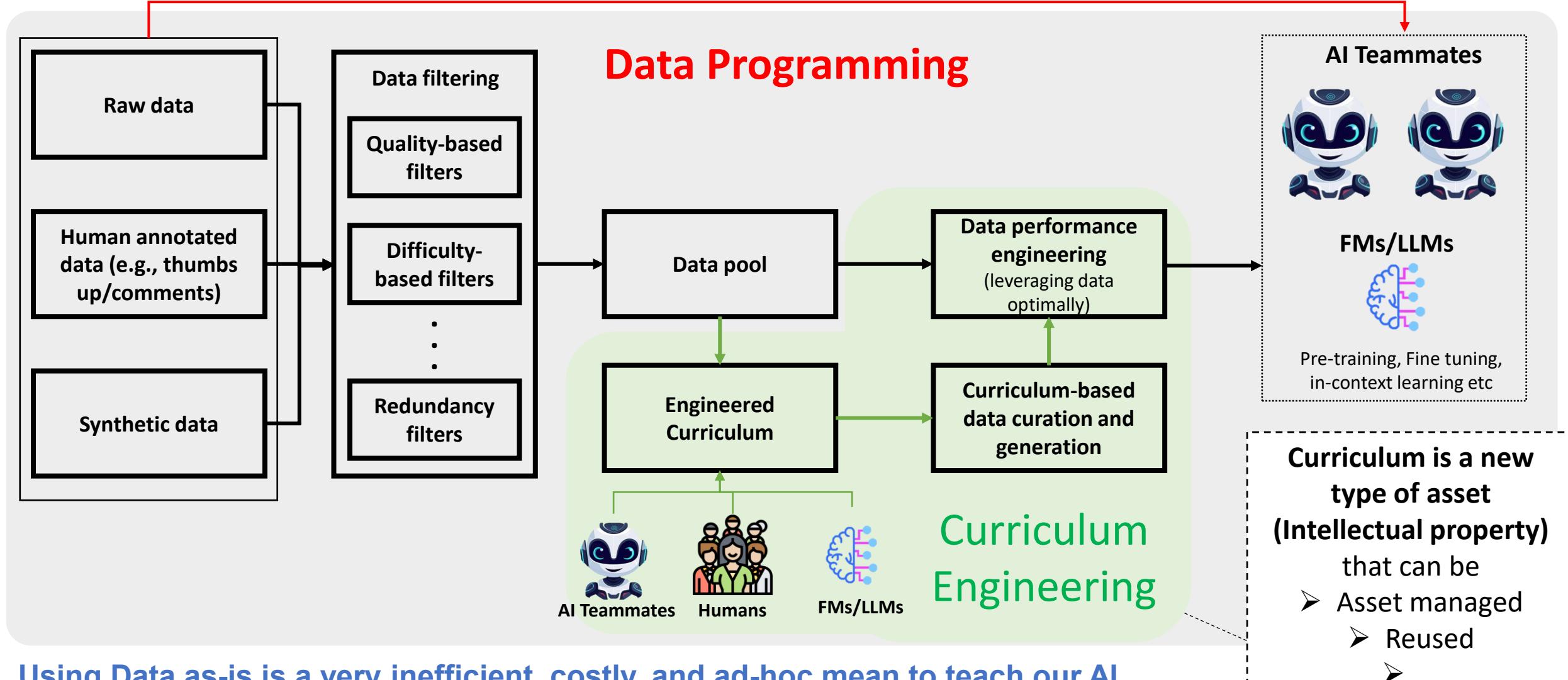
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# Data programming and engineered curriculums enable the efficient creation of better AI Teammates and FMs for SE 3.0

Traditional unsupervised data usage (inefficient)



Using Data as-is is a very inefficient, costly, and ad-hoc mean to teach our AI Teammates for SE. Instead, data programming and curriculum engineering are more effective and efficient ways of teaching our AI Teammates



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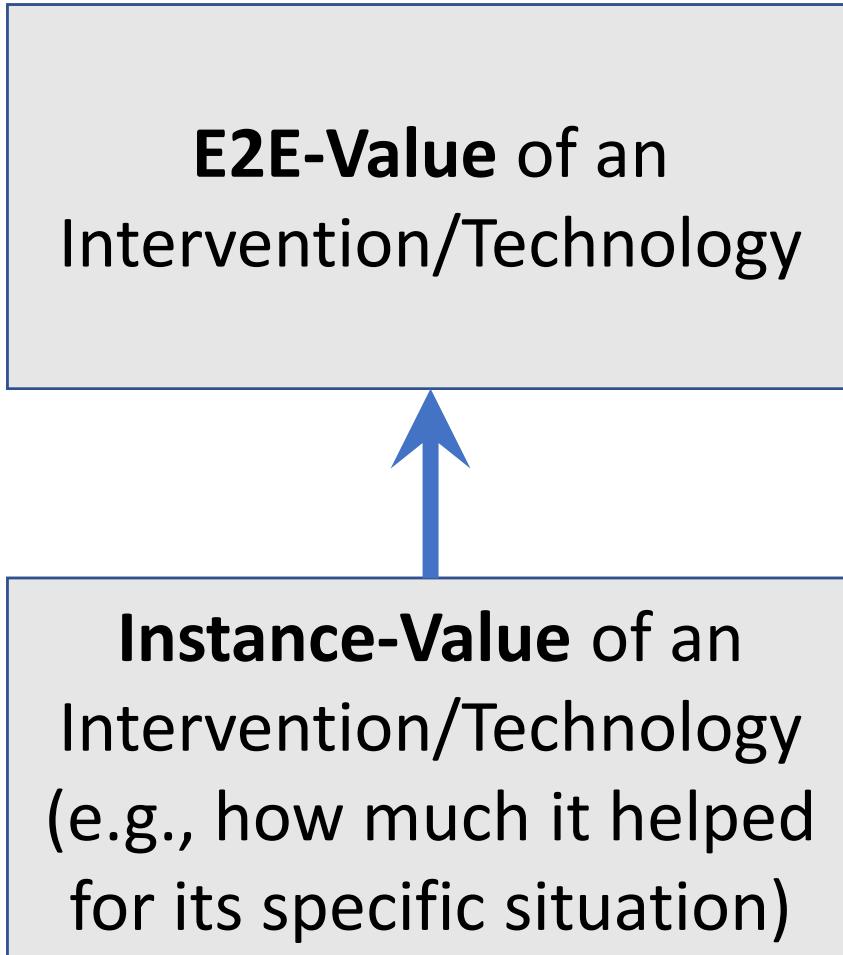
## ❑ Where are we today?

- ❑ **AI4SE:** A very shallow perspective on the ROI of AI4SE
- ❑ **SE4AI:** Too focused on AI models and prompting instead of AI systems

## ❑ Conclusion



# How to measure the value – especially e2e-value not just instance-value?!



A technology/intervention might help speed up coding, but then lead to

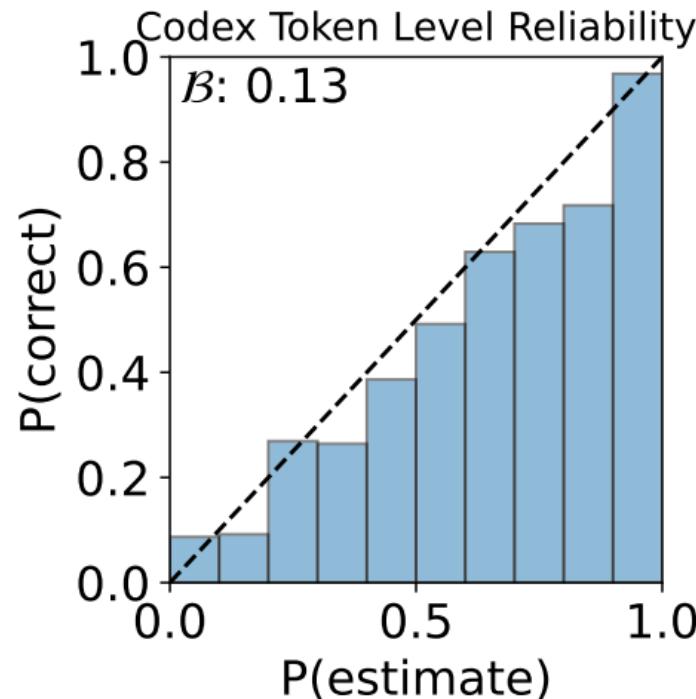
- Lower code health
- More bugs
- Negatively impact ability to release features faster enough
- Lost revenue \$\$

**E.g., how to quantify ROI of code-reviewing or AI4SE?**

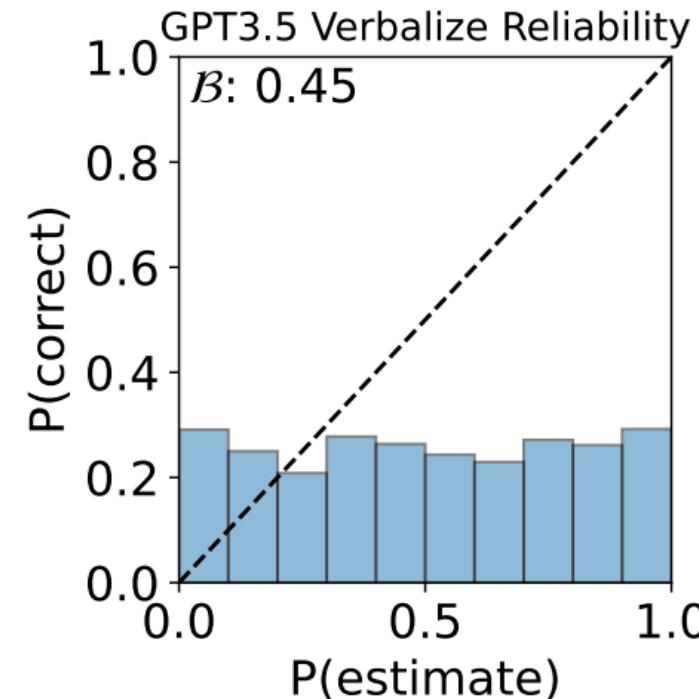
**Let us examine the Instance-Value of AI-coding**



# AI Code Completion: How much should you trust GPT's confidence in its answer?!



(a) Well Calibrated



(b) Poorly Calibrated

Weather Models need a minimum Brier of 0.05 to be considered for deployment (Brier of 0 is perfect prediction)



# A frank assessment of the reported ROI metrics of AI-coding: The realities of HumanEval

HumanEval is a benchmark dataset by OpenAI, to evaluate a model's ability to solve coding problems. It consists of 164 human-written *leetcode-like unrealistic* programming problems, each with a function description, code body, and unit tests in python.

The goal is to assess the model's understanding of natural language, algorithms, and basic math by making it generate code that fulfills the problem description and passes the tests.

## HumanEval Insights: Simple prompt experiment setup

- Simplest prompt (*baseline case*) Pass@1 = 0.84146
- Context enhancement:
  - Simplest prompt + code hints (e.g. ensure all imports, coding tips) Pass@1 = 0.9136
  - Simplest prompt + unit tests & expected outcomes Pass@1 = 0.9207
- Reasoning enhancement:
  - Simplest prompt + think 'step by step' (aka 0-shot-CoT) Pass@1 = 0.9329
- Trying it all together:
  - Simplest prompt + think 'step by step' + unit tests + code hints Pass@1 = 0.9268

\* simplest prompt = single call to LLM inference

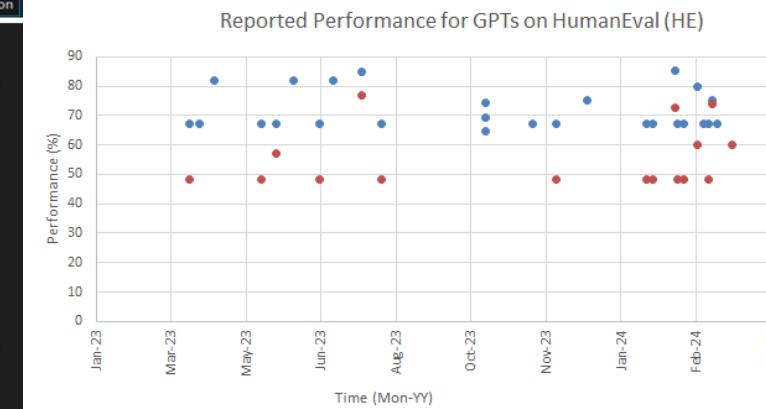
Bigger context is not necessarily better

- ❖ Very sensitive to prompting approach (~25% improvement by just prompt hacking!)

The screenshot shows a terminal window with Python code for generating AI completions. The code uses the `client.chat.completions.create` method with a `model=gpt-4-0125-preview`. The `messages` list contains two messages: one from the system role asking for help and one from the user role asking for examples from the HumanEval dataset. The response is generated in 26.1s and is displayed below. The text discusses the HumanEval dataset and provides two examples: Fibonacci Sequence and Palindrome check.

```
response = client.chat.completions.create(
    model="gpt-4-0125-preview",
    messages=[{"role": "system", "content": "You are a helpful AI assistant. Answer questions to your best ability. If you don't know the answer, simply state that you do not know."}, {"role": "user", "content": "Can you give me some examples from HumanEval dataset please?"}, ]
)
[{"role": "assistant", "content": "Certainly! The HumanEval dataset, also commonly referred to as the Codex dataset, consists of Python programming problems designed to evaluate code generation models. These problems include a wide range of tasks, from string manipulation to more complex algorithmic challenges. Each problem in the dataset is accompanied by a function signature, a docstring explaining what the function should do, and several test cases.\n\nHere are a few example problems from the HumanEval dataset:\n\n### Example 1: Fibonacci Sequence\n**Problem:** Write a function to calculate the nth Fibonacci number.\n\n```python\ndef fibonacci(n: int) -> int:\n    """Given n, return the nth Fibonacci number. For example, fibonacci(0) = 0, fibonacci(1) = 1, fibonacci(2) = 1, fibonacci(3) = 2.***\n    pass\n```\n\n### Example 2: Check if Palindrome\n**Problem:** Write a function to determine if a given string is a palindrome.\n\n```python\ndef is_palindrome(s: str) -> bool:\n    """Given a string s, return True if it is a palindrome, False otherwise.\n    A palindrome is a string that reads the same forward and backward.\n    Examples: 'racecar', 'level', 'rotator'.\n    ````\n    pass\n```\n\nThese examples illustrate the type of problems found in the HumanEval dataset, which requires the model to understand natural language instructions and generate correct Python code to solve them."}]
```

- ❖ Already contaminated in most FMs today .. ChatGPT has the examples in its training data



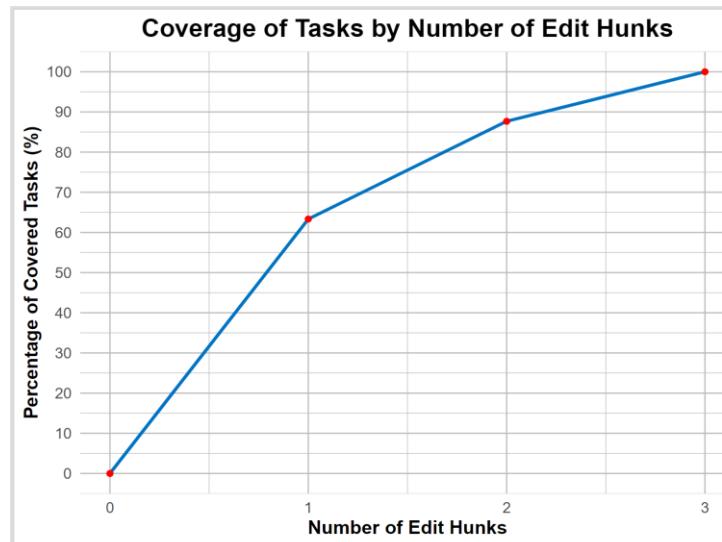
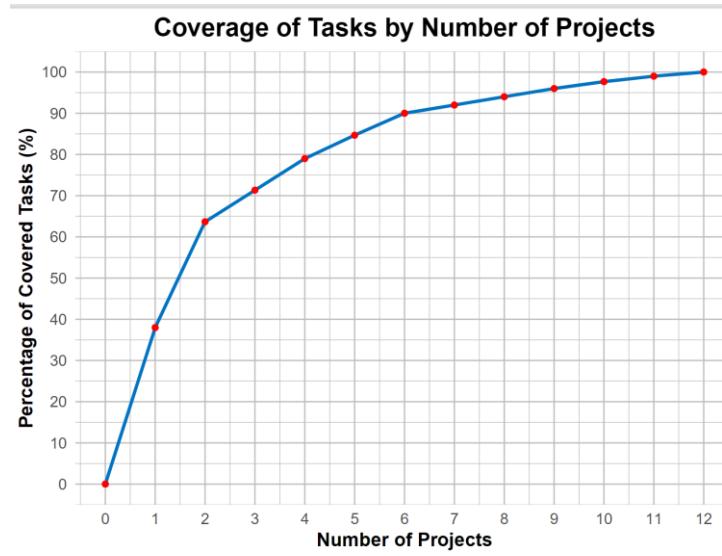
● HE,GPT-4  
● HE,GPT-3.5



# A frank assessment of the reported ROI metrics of AI-coding: The realities of the SWEbench

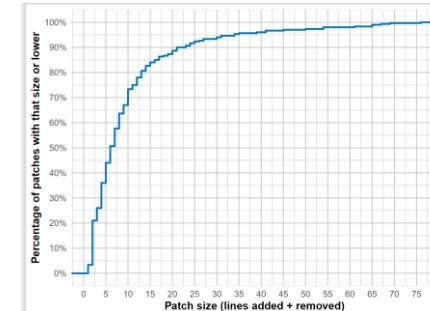
SWEbench is a real-life projects dataset that is designed to evaluate a system's capability to automatically resolve GitHub-level issues.

Researchers use this dataset to see if new advancements in FMs can be applied to real-world SE tasks



- ❖ 65% of SWEbench lite comes from just 2 projects:
  - ❖ Sympy: a python-based symbolic execution framework
  - ❖ Django: a python-based web-creation framework

- ❖ 100% of SWEbench lite issues impact a SINGLE file ONLY
- ❖ 2/3 of SWEbench lite issues just changed ONE area in that ONE file
- ❖ 90% of issues changed <20 LOC



# % of accepted suggestions

a common industry metric fails to consider many factors

[We can achieve **100%** if one simply suggests the “;” at the end of each line of Java code]



30% of keystrokes (attempt opportunities) are in middle of an already written-code line! Many AI4coding systems will not attempt a completion in such a setting, as chances of success today are low

The latency of the AI4coding system is crucial; speed of model inference & speed of context creation matter considerably

The classical % of accepted suggestions

The size of the suggestion – one can take a large suggestion and split it into smaller suggestions (some time even desired – Meta reports developer preferring shorter suggestions otherwise they mentally move from coding to code reviewing)

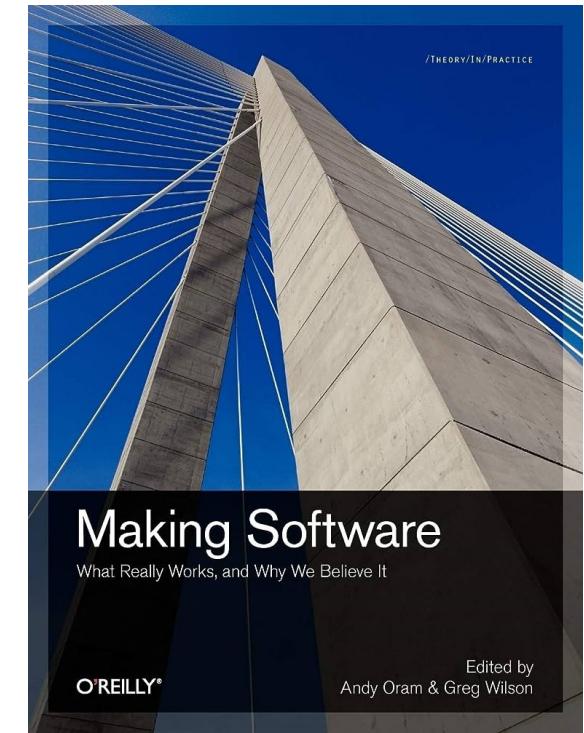
**Characters per Opportunity =**  
**% of times AI attempted \* % of times an AI-attempt reaches a developer in time \***  
**% of reached-attempts that are accepted \***  
**Size of attempts**

An accepted attempt does not mean correct code, so we must consider how much of that code was eventually **integrated as-is** vs was **heavily modified!**



# Developer Productivity varies widely across individuals & activities (aka change-requests)

- As early as 1968, Sackman, Erickson and Grant show as much as 28 X difference in productivity (highest is for debugging activities)
- The 10 X difference in productivity between developers is well documented [see Chapter in Making Software by Steve McConnell, author of the Code Complete series]



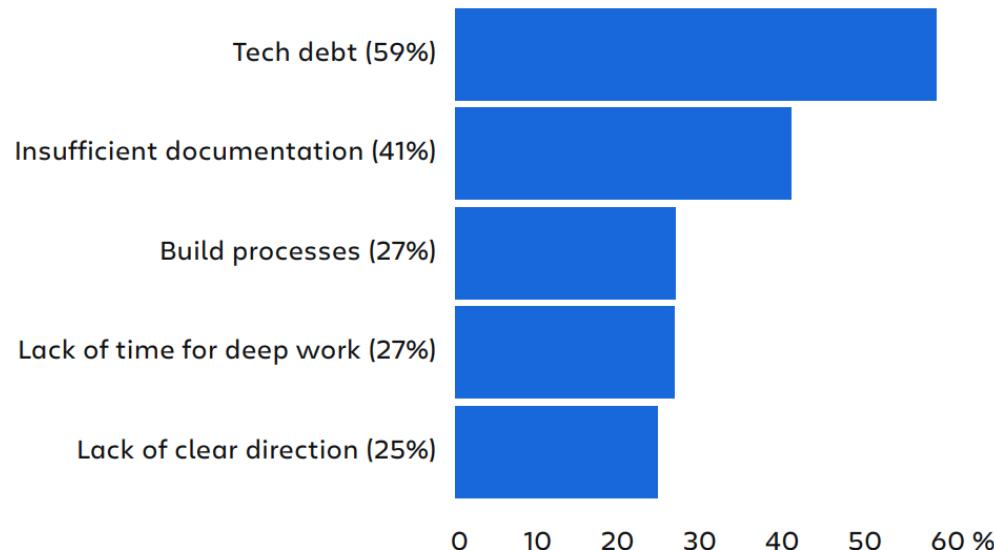
Somali runner sets record for 'slowest ever' 100m after taking over 20 seconds to complete:  
<https://www.youtube.com/watch?v=scMs2HSsFqg>

Hassan et al., Alware Leadership Bootcamp, Toronto, Canada, 2024



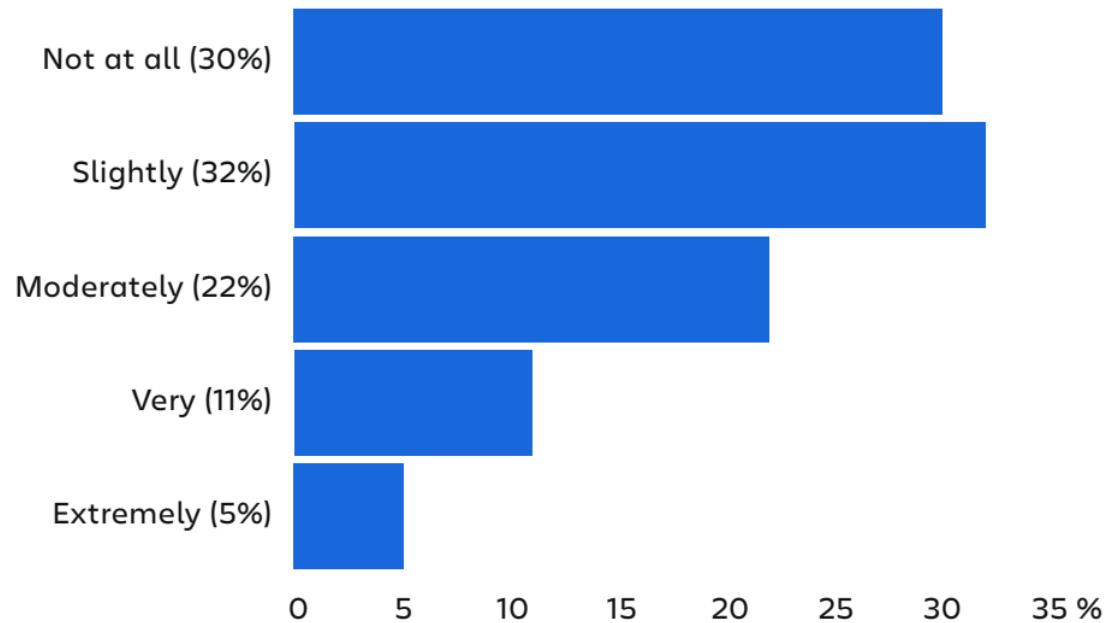
# The value of AI on Developer Productivity varies between leaders and developers

## Top 5 areas of developer-time loss according to developers



## How much are AI tools improving your productivity as a developer today?

**62%** of developers report slight to no productivity improvement from AI-based dev tools, **despite leadership's belief that using AI is the one of the most effective ways to improve productivity**



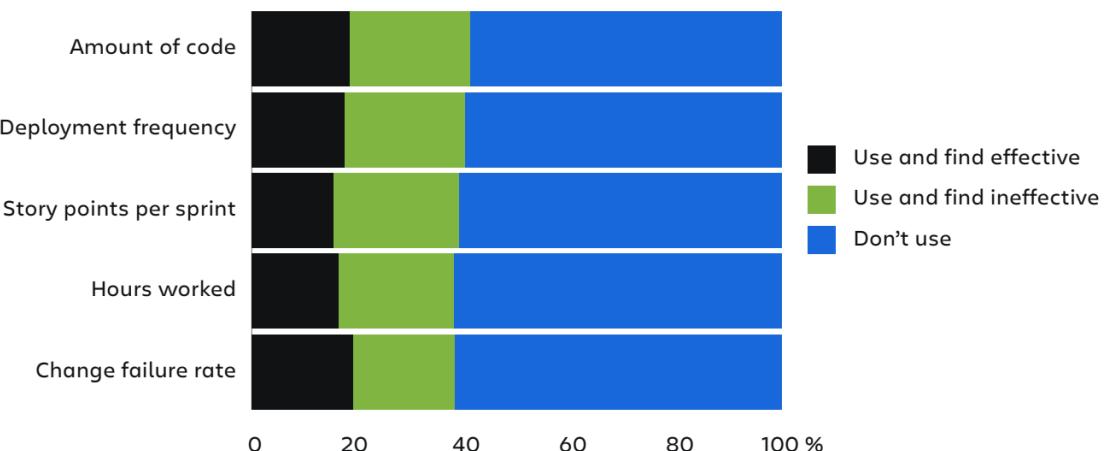
# Developer Productivity is quite hard to quantify

- One thing is clear – **NO PROJECT EVER FAILED because developers could not code fast enough!!**
- Short term improvement leading to higher technical debt (and higher long term costs)
- Less than 50% believe in the effectiveness of how they measure productivity
- The only thing we know today is that a happy developer is one that perceives that they are productive [MSFT/GitHub/ Atlassian Global surveys/...]

Meanwhile, there's a significant body of research showing that **happy workers** are productive workers. So instead of worrying about what makes developers more efficient, what if we think about what makes them **happy**? Not the surface-level **happiness** you can buy with high-dollar swag and on-tap kombucha, but the deep sense of fulfillment that comes from creating something great.

RAJEEV RAJAN Chief Technology Officer at Atlassian

## Top 5 ways organizations measure productivity and the effectiveness of such measures



Based on two surveys of 2K+ developers across the world commissioned by Atlassian in Feb 2024: 1) Wakefield Research surveyed 1,250 engineering leaders in the US, Germany, France, and Australia. 2) DX surveyed 900 developers around the world, including the US, Germany, France, and Australia.\* \*DX also surveyed developers in the UK, Sweden, Lithuania, Estonia, Spain, Ireland, Ukraine, Denmark, Switzerland, the Czech Republic, Canada, Brazil, and India.

Hassan et al., Alware Leadership Bootcamp, Toronto, Canada, 2024



# **Volvo's Mission to Software Excellence: AI4SE is more than just saving keystrokes!**



*tricky to keep focus.. Lots of context switching..*

*More time to be creative*

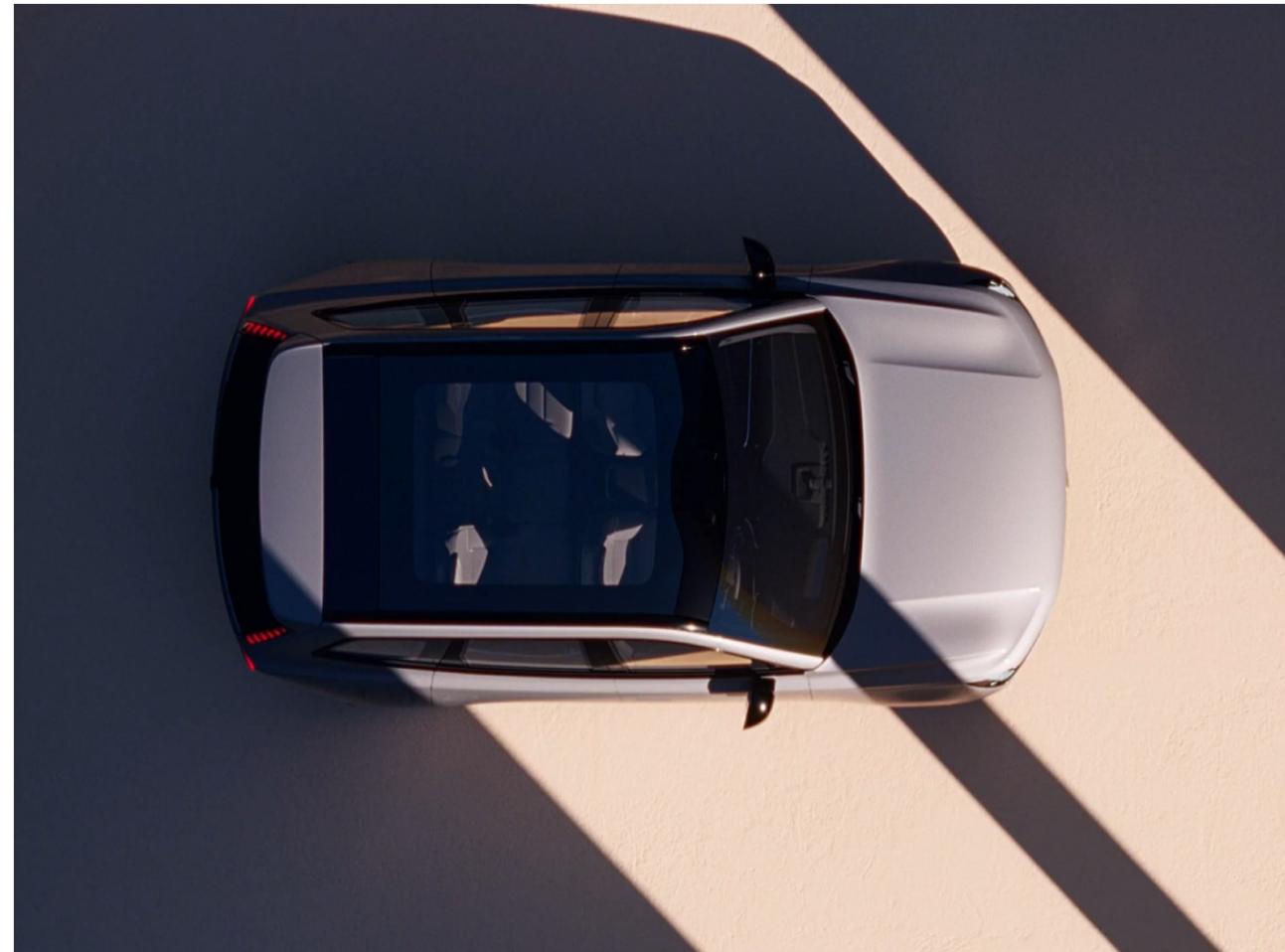
*Wow, it does all the boring stuff for me..*

*It teaches me stuff, I learn how to..*

*It suggests things I would not come up with myself*

*I am learning more when using it*

*Signals we are getting are positive!*



# The time respondents save with AI is being used to collaborate, learn, and design systems

TASKS RESPONDENTS ARE ABLE TO SPEND MORE TIME DOING AFTER USING AI CODING TOOLS

	USA N=497	BRAZIL N=495	GERMANY N=485	INDIA N=496
<span style="color: pink;">█</span> COLLABORATING WITH TEAM MEMBERS ON PROJECTS	<u>47%</u>	46%	<u>47%</u>	40%
<span style="color: pink;">█</span> DESIGNING SYSTEMS & CUSTOMER SOLUTIONS	<u>47%</u>	42%	<u>47%</u>	40%
<span style="color: purple;">█</span> LEARNING & DEVELOPMENT	46%	<u>47%</u>	43%	<u>44%</u>
<span style="color: blue;">█</span> RESEARCHING & EXPERIMENTING WITH EMERGING TECHNOLOGY	46%	44%	45%	<u>44%</u>
<span style="color: lime;">█</span> CODE REVIEW	42%	45%	39%	43%
<span style="color: yellow;">█</span> REFACTORING & OPTIMIZING CODE	37%	42%	43%	37%
<span style="color: orange;">█</span> TAKING BREAKS	34%	29%	31%	33%

Which of the following are you able to spend more time doing due to using AI coding tools at work? Please select all that apply.

*Note: Underlined data indicates the highest common survey responses.*



# Let us dig deeper into AI-coding through extended user studies

- Long term use quantification: (intuition if developers continue using it then they must see value of it.. Contrast to smoking – most smokers will continue smoking!)
  - ~5% of developers use AI-coding and around 63% of them use it as just codecomplete++ [Sourcegraph developer of Cody AI-coding tool, June 2024]
- ~20% not 10X acceleration of productivity (aka doing tasks faster) [18% features, 26% bug-fixes]
  - 75% less code for features but 71% more code for bug-fixes [due to ease of adding more test cases] – *if you use LOC for productivity it will give conflicting signals*
  - 17% of **code “tokens”** are coming from copilot
- The impact on code health is not promising
  - 5X increase in chances to introduce cloned code!
  - 25X increase in chances to introduce vulnerabilities!
  - Do note: we did not quantify whether it introduced more bugs – we can fix bugs faster though!



# Key take home:

- It is really hard to quantify ROI
- Just measure developer happiness!

It is not advisable to run an SE organization based on a happiness measure!



**SE 1.0**  
**(Code-First  
+Trad non-AI SE Tooling)**

Punch-Card  
Era

Platform  
Powered

**SE 2.0**  
**(Code-First  
+ AI4SE Tooling)**

Model-  
Centric

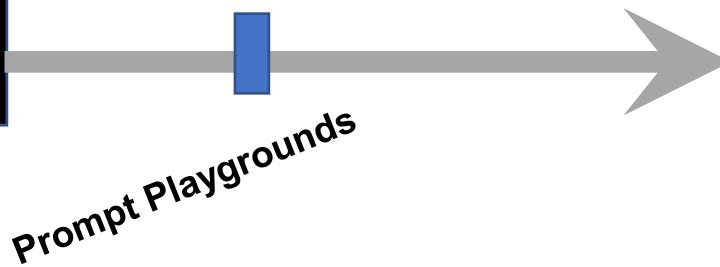
AI-System  
Centric

**SE 3.0**  
**(Intent-First  
+AI-Native SE)**

Curriculum  
Powered

Self-  
Evolving AI

Indus-  
try



Prompt Playgrounds

SOTA



LangGraph+  
LangSmith

CSE



FMArts 1.0  
FMArts 1.5

## State of SE for FMware (i.e., FM/LLM- Powered Software)

FMArts 3.0  
Late 2025

FMArts 3.5  
2026+



**SE 1.0**  
**(Code-First**  
**+Trad non-AI SE Tooling)**

**SE 2.0**  
**(Code-First**  
**+ AI4SE Tooling)**

**SE 3.0**  
**(Intent-First**  
**+AI-Native SE)**

Punch-Card Era

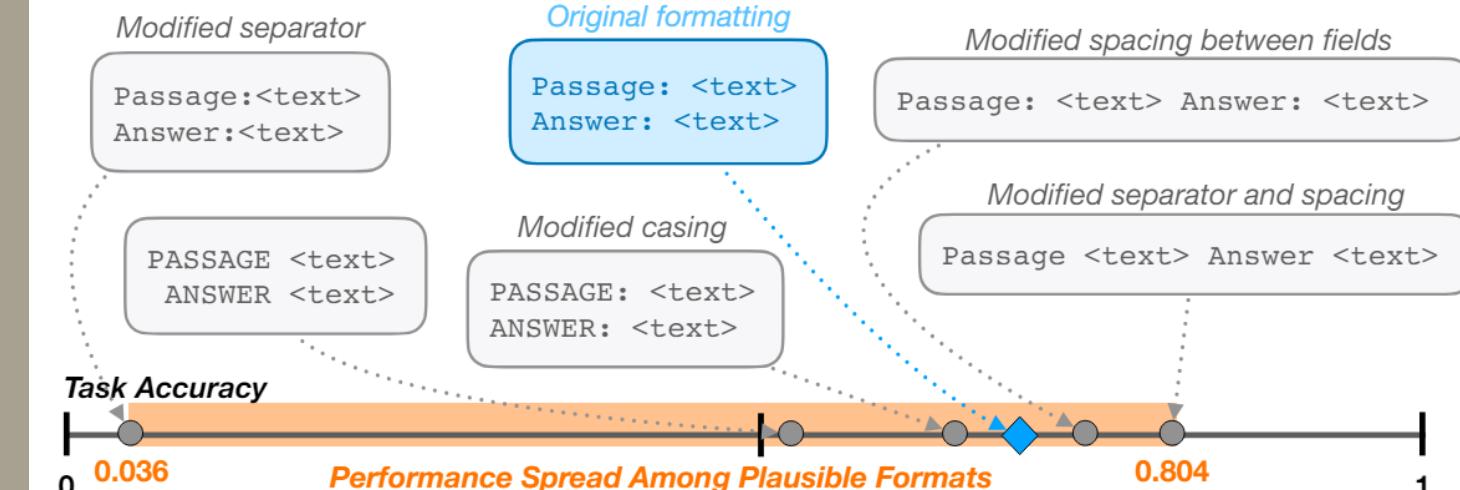
Why are we skipping FMArts 2.0?  
Prompting is too unstable and not portable

Self-Evolving AI

Industry

Prompt Editors

SOTA

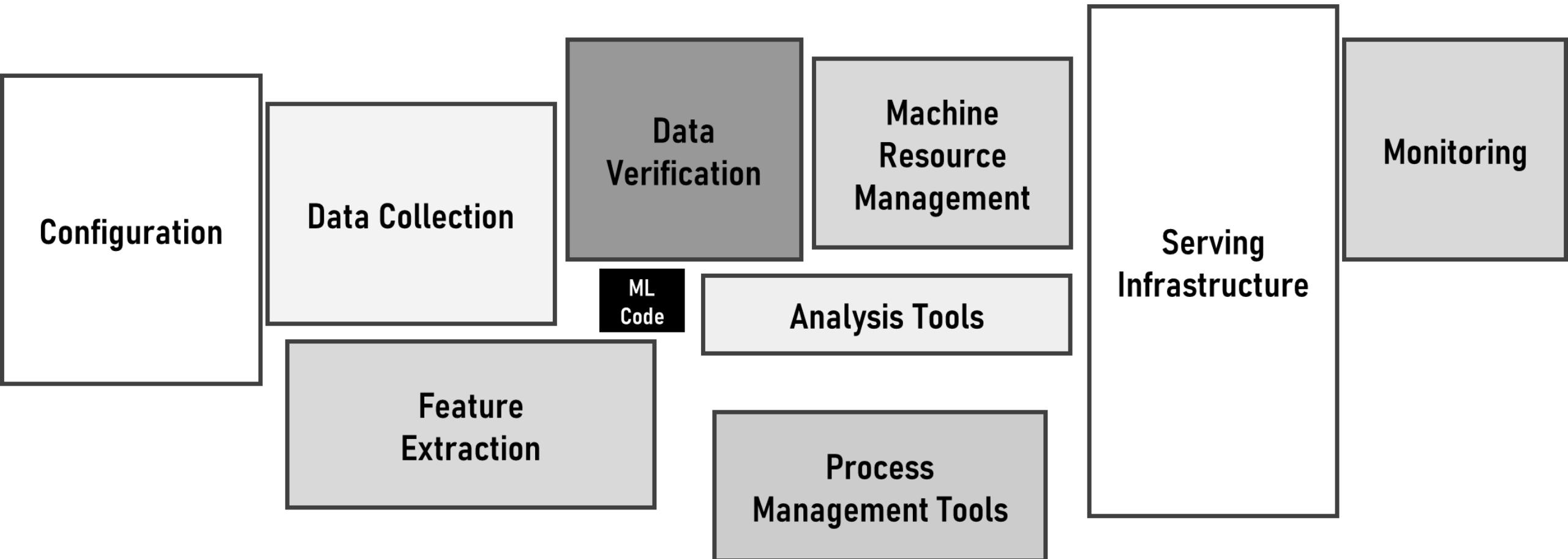


of SE for  
ware  
M/LLM-  
Software)



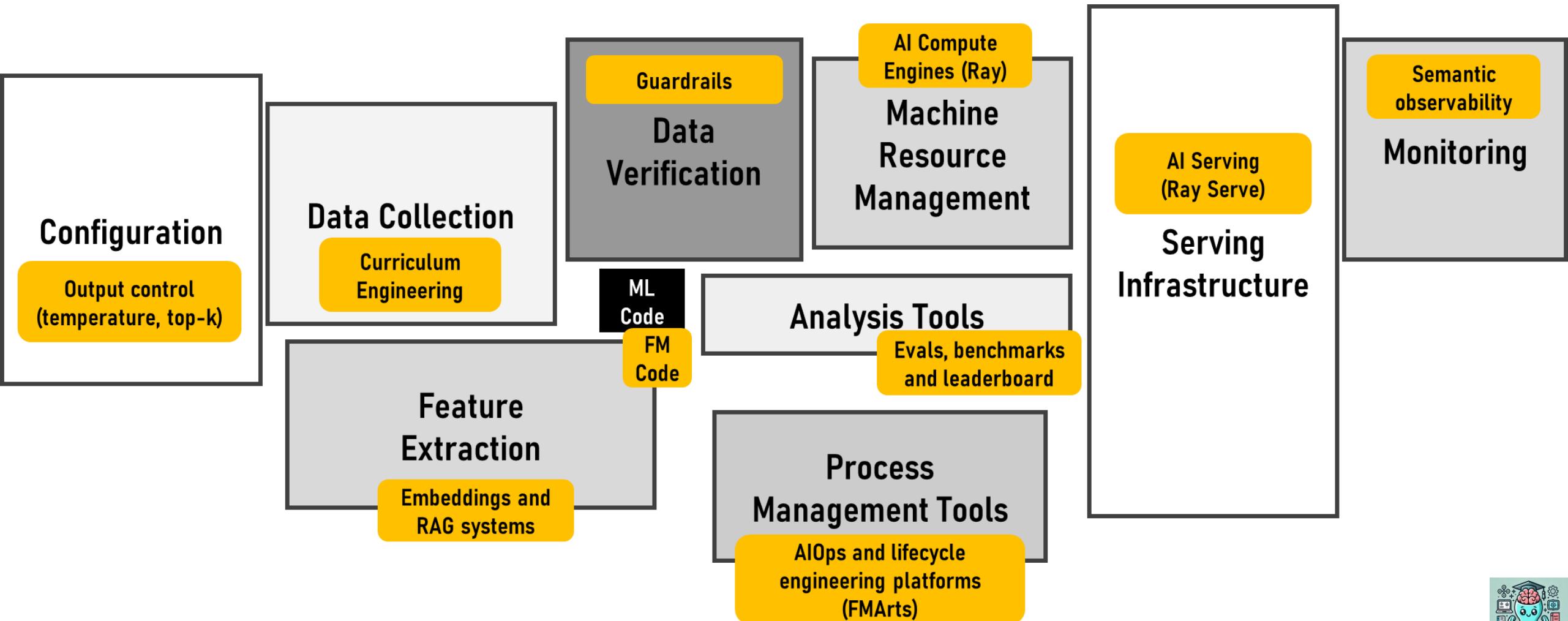
# Over-focusing on the model itself is a repetition of traditional AI engineering pitfalls

"Models are only a small part of AI systems"



# Over-focusing on the model itself is a repetition of traditional AI engineering pitfalls

"Models are only a small part of AI systems"



# Overview of the session

## ❑ Rethinking Software Engineering

- ❑ Software eras
- ❑ Software engineering eras
- ❑ Towards AI-native SE: our vision and technology stack

## ❑ Where are we today?

- ❑ AI4SE: A very shallow perspective on the ROI of AI4SE
- ❑ SE4AI: Too focused on AI models and prompting instead of AI systems

## ❑ Conclusion



# Key Take homes

- Thinking of model inference and LARGER models is the same as thinking of FLOPS, they mean nothing for value → NEED an AI system perspective and e2e value perspective
- Must re-think SE and Software to be AI-native, coding was never the problem instead it is the recognition and realization of Intents
- Prompt ~~Engineering~~ Hacking MUST die ☺



Teammate.next

Personalized AI partners

IDE.next

(Developing, Debugging, Maintaining)  
Intent-First + Conversational

Compiler.next

Code realization through  
synthesis and search

Runtime.next

SLA-aware Uni-Cluster Runtime  
with Edge Extension

FM.next

Curriculum engineered models





## Teammate.next

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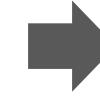
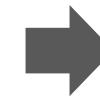
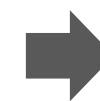
SLA-aware Uni-Cluster Runtime  
with Edge Extension

## FM.next

Curriculum engineered models

## SE 2.0

- Static
- Impersonal
- Code-Centric
- Editing
- Logic-Rule Realization
- Serving Models
- Data-driven Inefficient FMs



## SE 3.0

- Self-Evolving
- Personalized Mentor
- Intent-Centric
- Conversations
- Search-Space Exploration
- Serving Compound Apps (Alware)
- Knowledge-driven Efficient FMs

