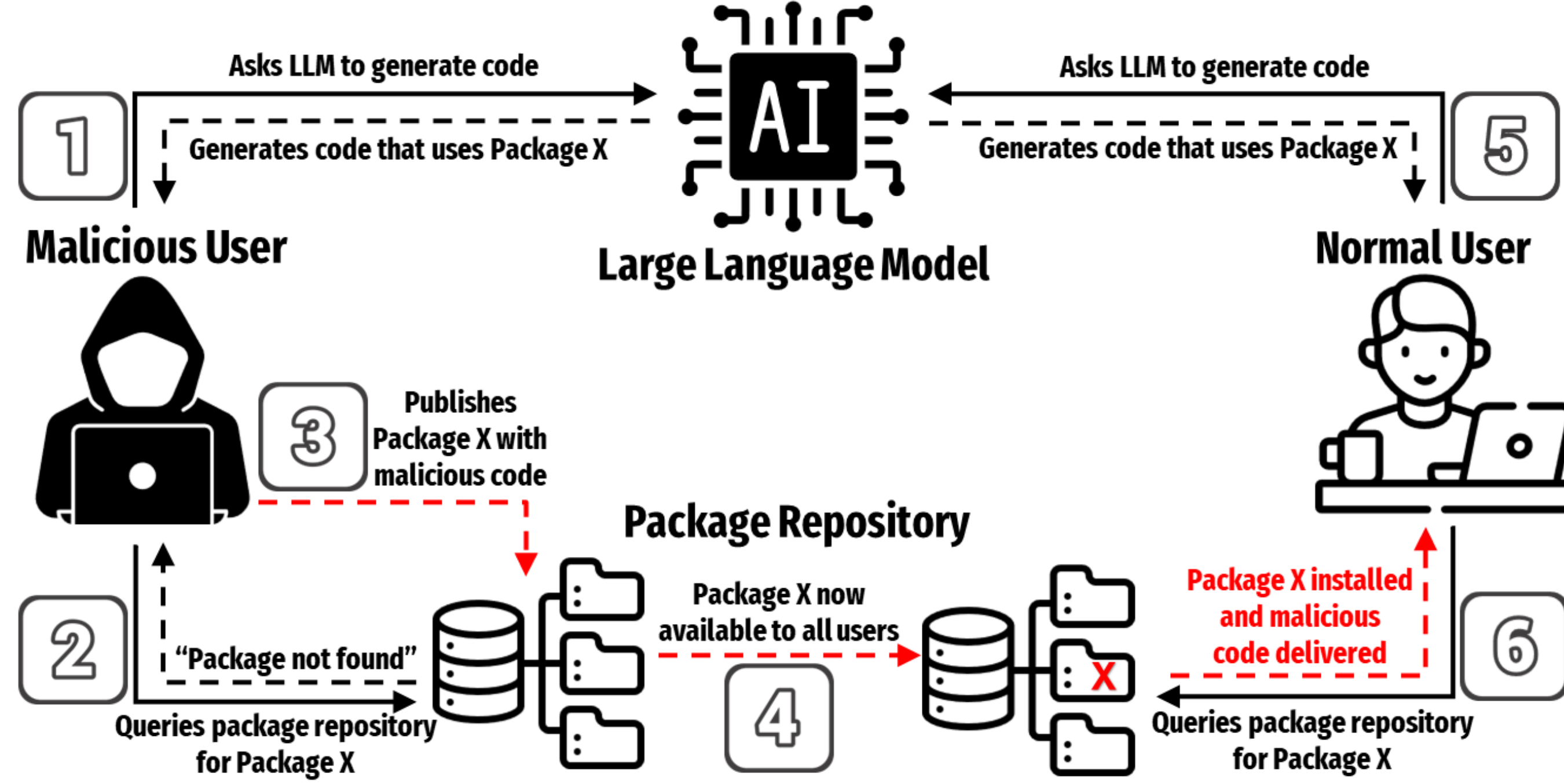
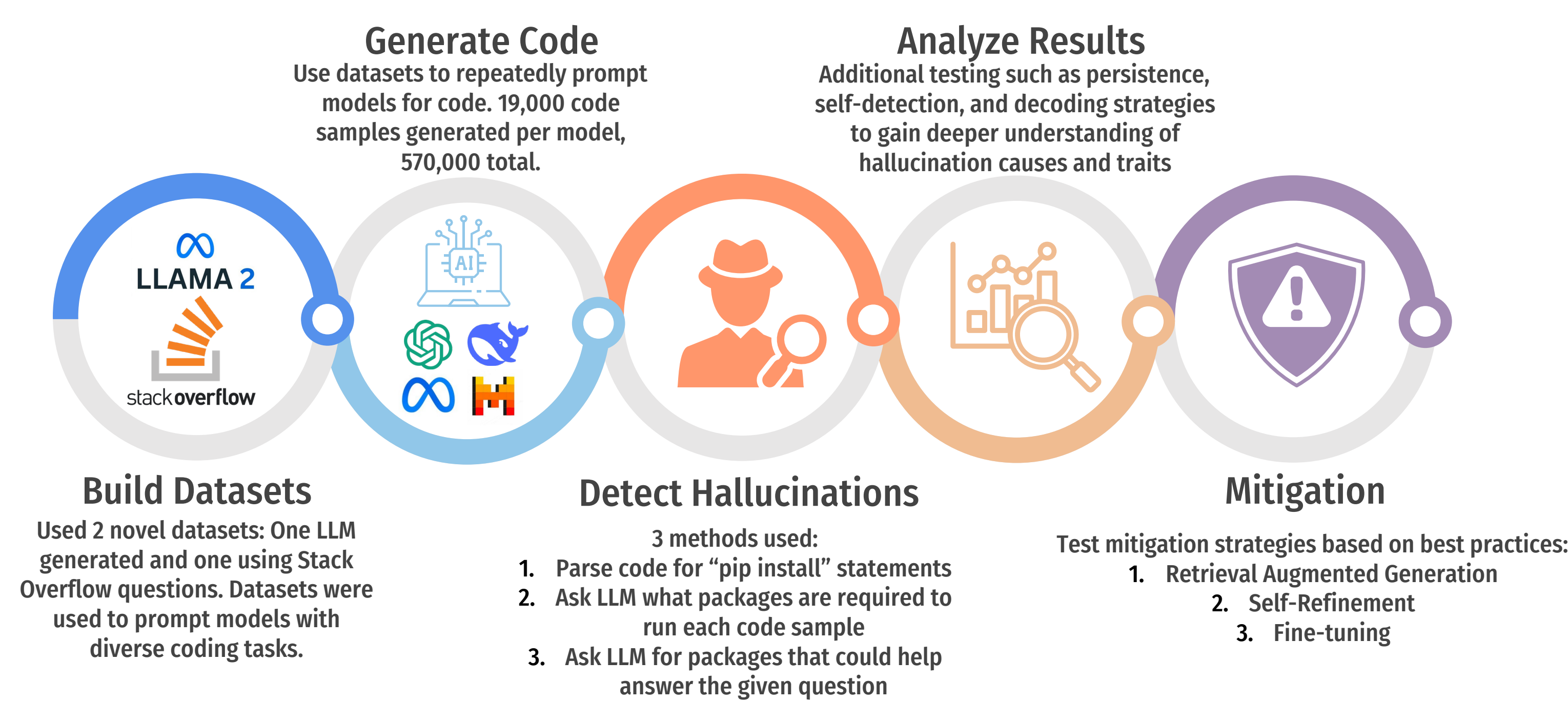


## Package Hallucination Attack



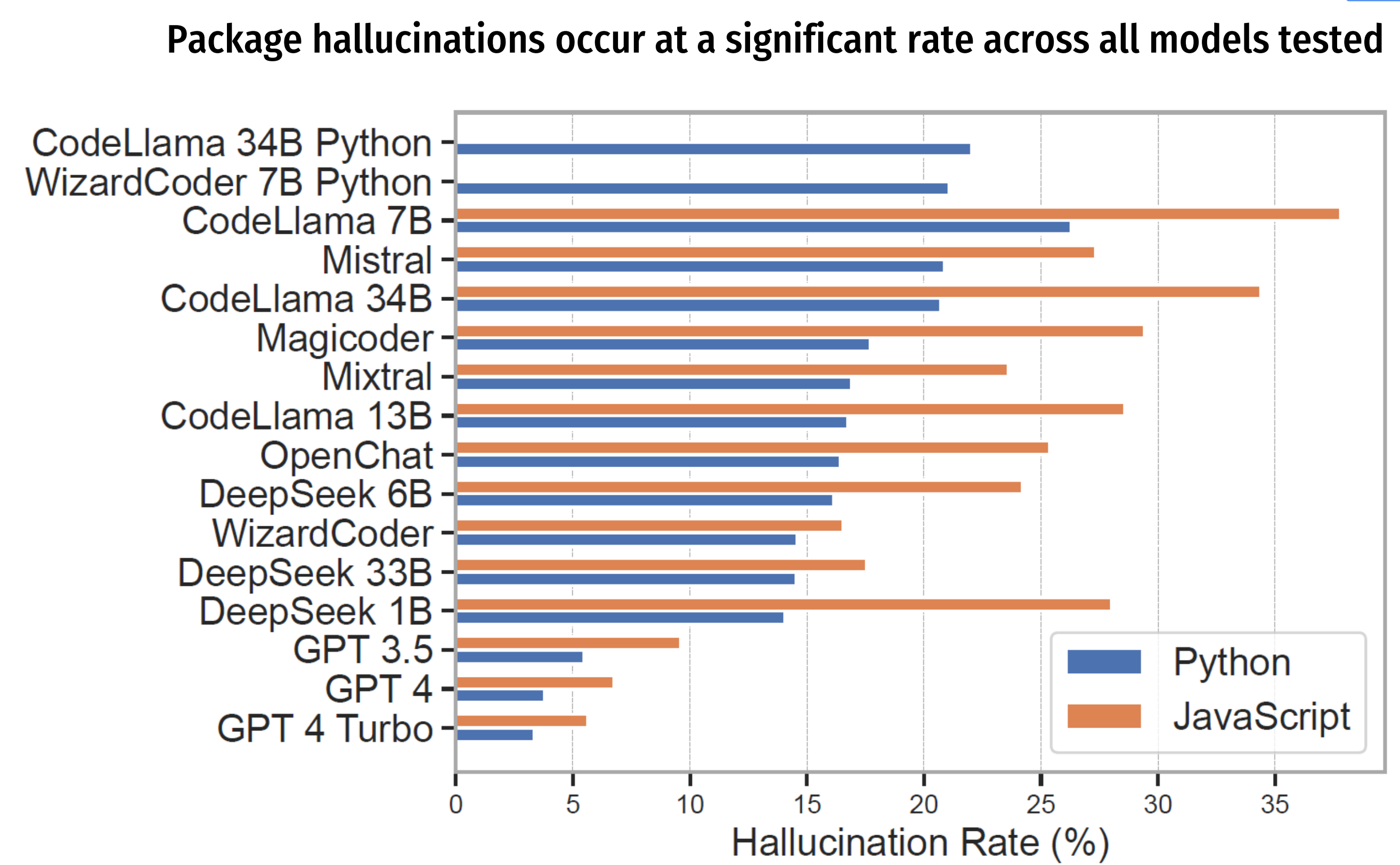
## Experiment Design



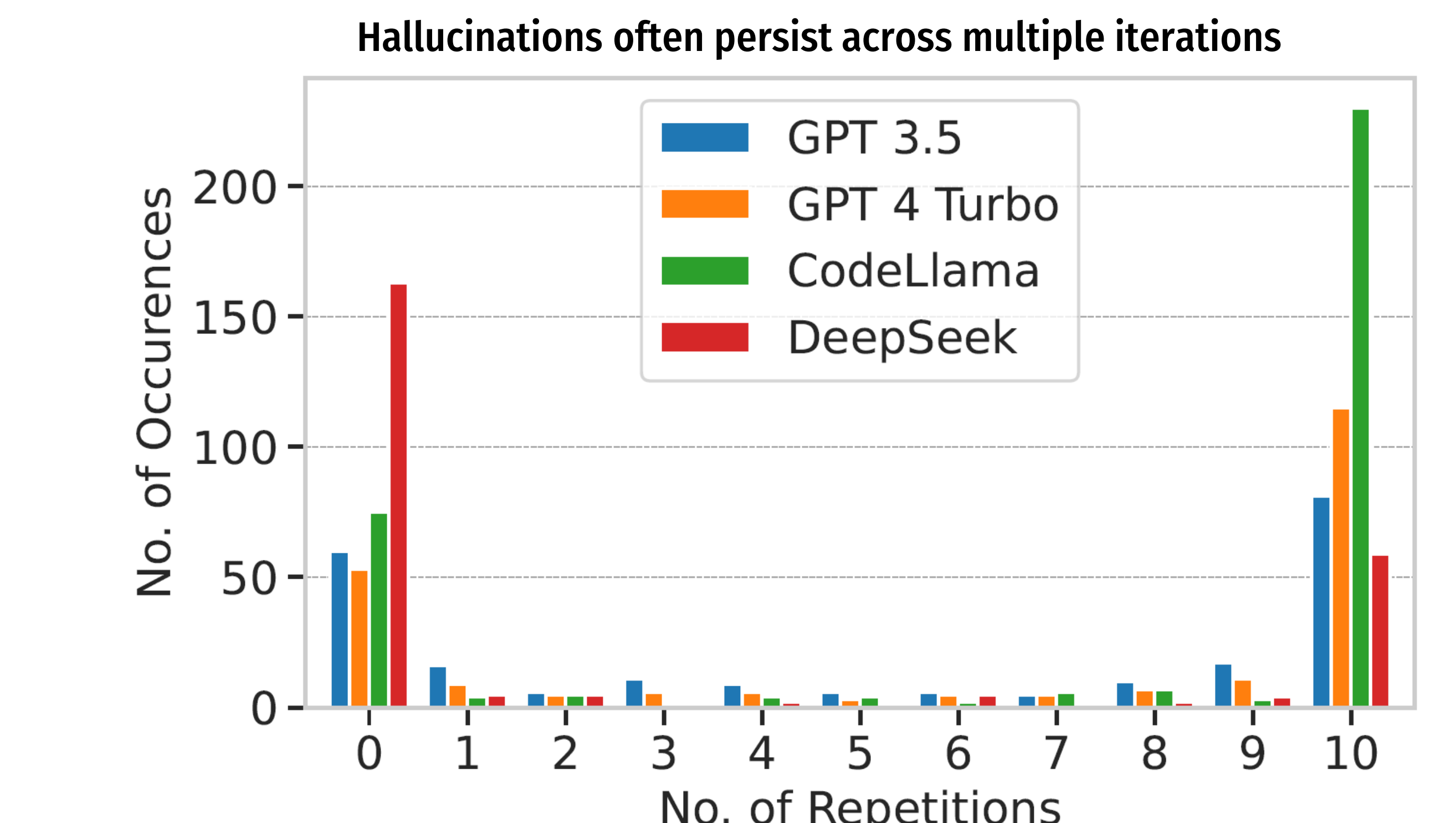
## Models Tested

Number of Parameters	1B	7B	14B	34B	70B+
OpenAI					●●●
code llama		●	●	●	●
deepseek	●	●	●	●	
MISTRAL AI_		●		●	
ISE Magicoder		●			
WizardCoder	●	●		●	

## 01 PREVALENCE



## 02 PERSISTENCE



## Key Findings

### 01 Prevalence

- 19.4% of all packages generated were hallucinated (i.e. non-existent, fictitious)
- 205,474 unique hallucinated package names were generated

### 02 Persistence

- 48% of the time a hallucinated package will be repeated when given the same prompt
- A hallucination will repeat within 10 iterations 60% of the time

### 03 Self-Detection

- 3 out of 4 models were able to correctly identify their own hallucinations more than 75% of the time

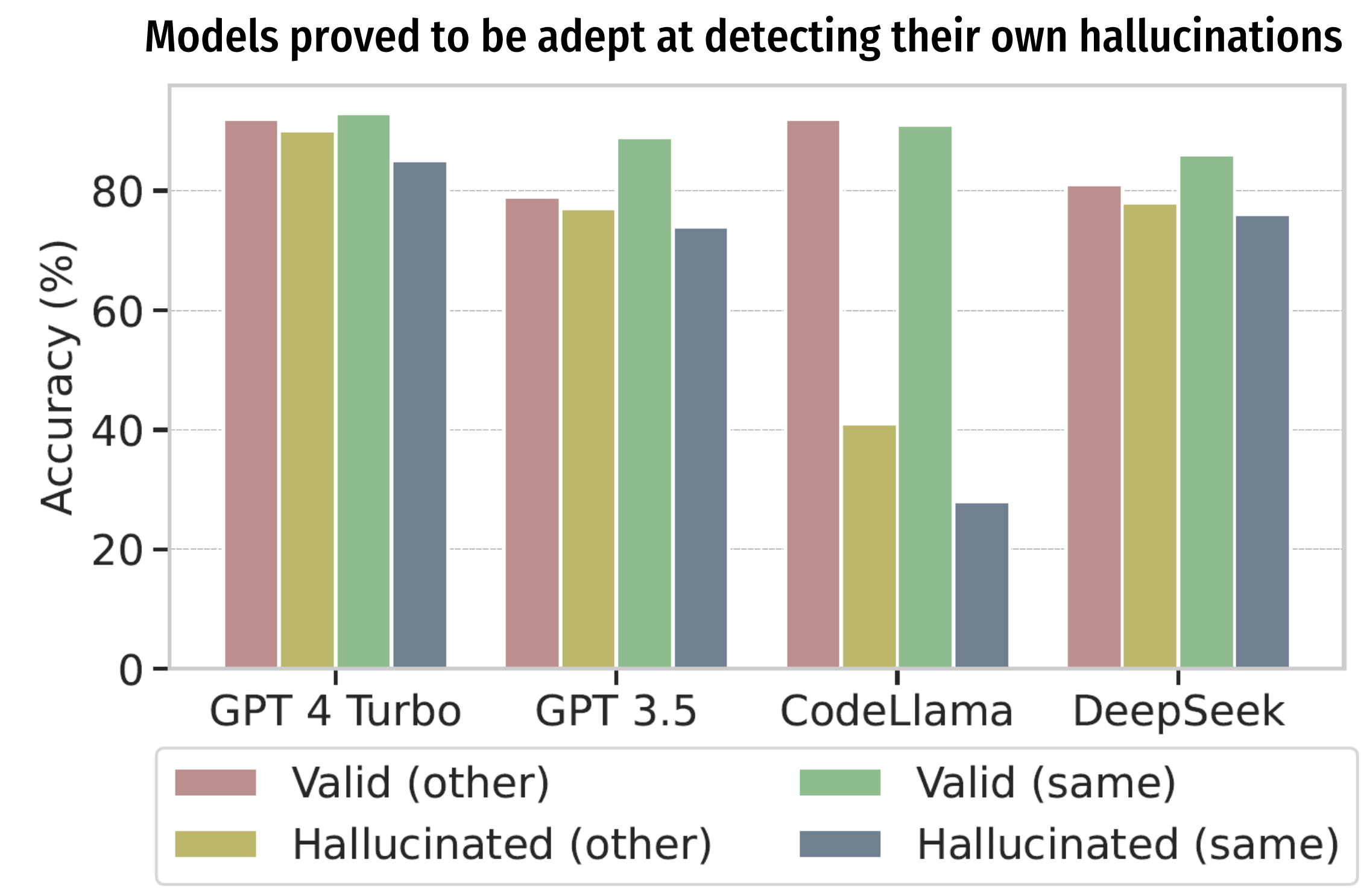
### 04 Decoding Strategies

- Higher temperatures dramatically increase hallucinations
- Package hallucinations are usually generated by the most probable tokens

### 05 Mitigation

- Fine-tuning is an extremely effective mitigation strategy for package hallucination
- Combining mitigation methods brings hallucination rate below ChatGPT

## 03 SELF-DETECTION

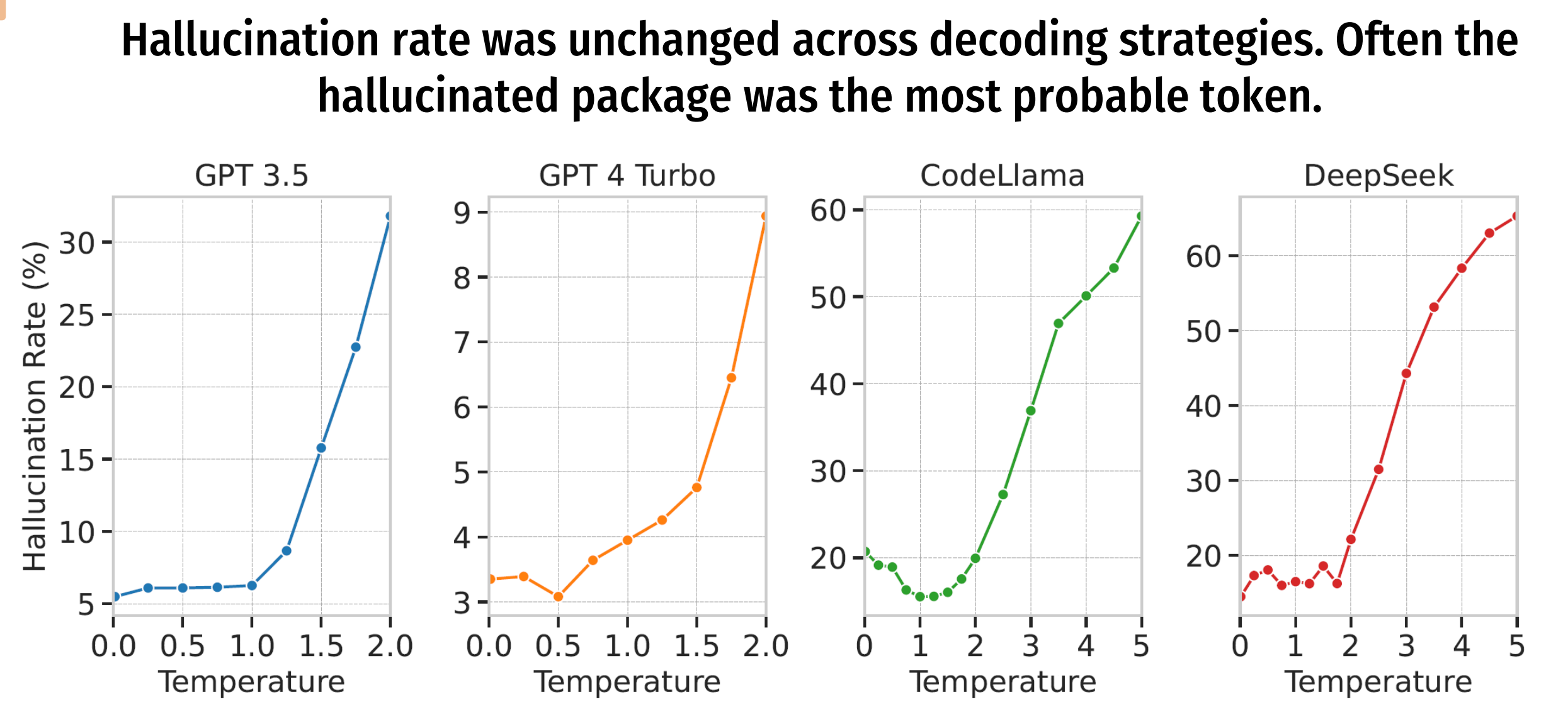


## 05 MITIGATION

Hallucinations were reduced using best practices but not eliminated

	DeepSeek	CodeLlama
Baseline (No Mitigations)	16.14%	26.28%
Retrieval Augmented Generation (RAG)	12.24%	13.40%
Self-Detected Feedback	13.04%	25.51%
Fine-tuning	2.66%	10.27%
Ensemble	2.40%	9.32%

## 04 DECODING STRATEGIES



Altering decoding strategies produced higher hallucination rates in all cases

	DeepSeek	CodeLlama
Baseline (Default Decoding)	16.14%	26.28%
Top-k Lower	17.1%	27.8%
Top-k Higher	18.1%	28.3%
Top-p Lower	17.5%	28.0%
Top-p Higher	18.4%	28.3%
Min-p Lower	17.8%	27.9%
Min-p Higher	19.2%	28.6%