# An In-Depth Look at Baidu's Al Aspirations

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**NEWSHA ARDALANI** 













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### Bai 也大脑 Baidu Brain

# AI&HPC

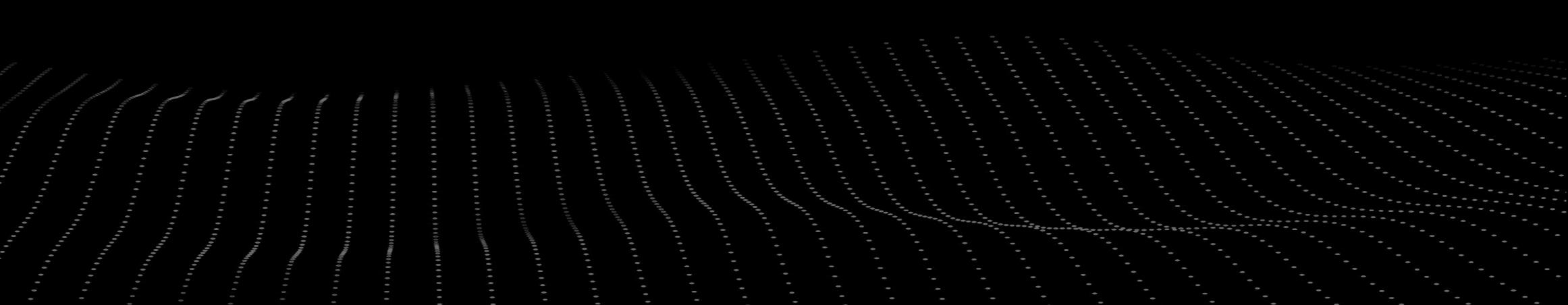
### Make communication easier

- Speech Recognition
- Text-to-Speech Synthesis
- Simultaneous Translation
- Language Model

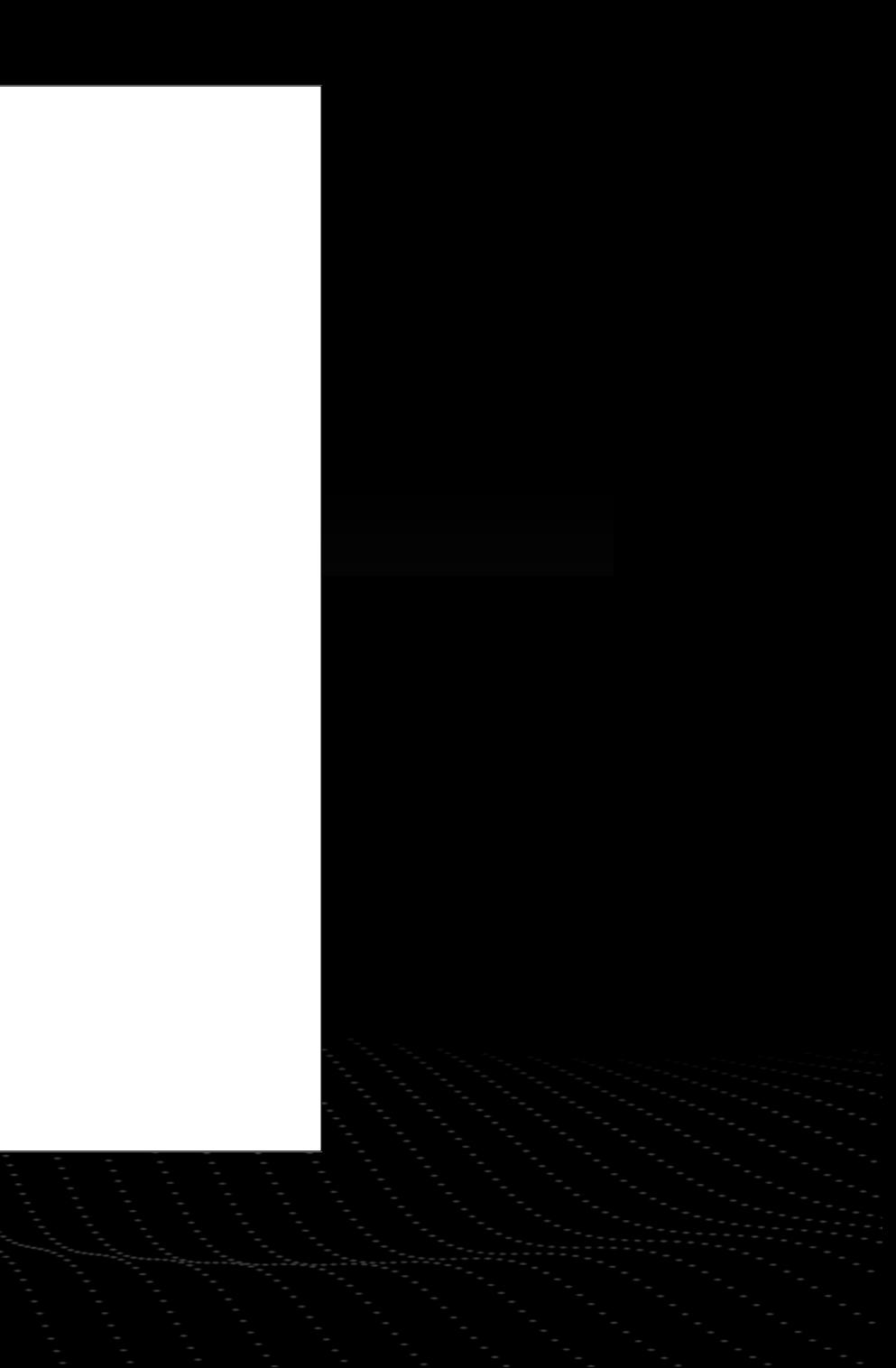


### Make AI faster

High Performance Computing





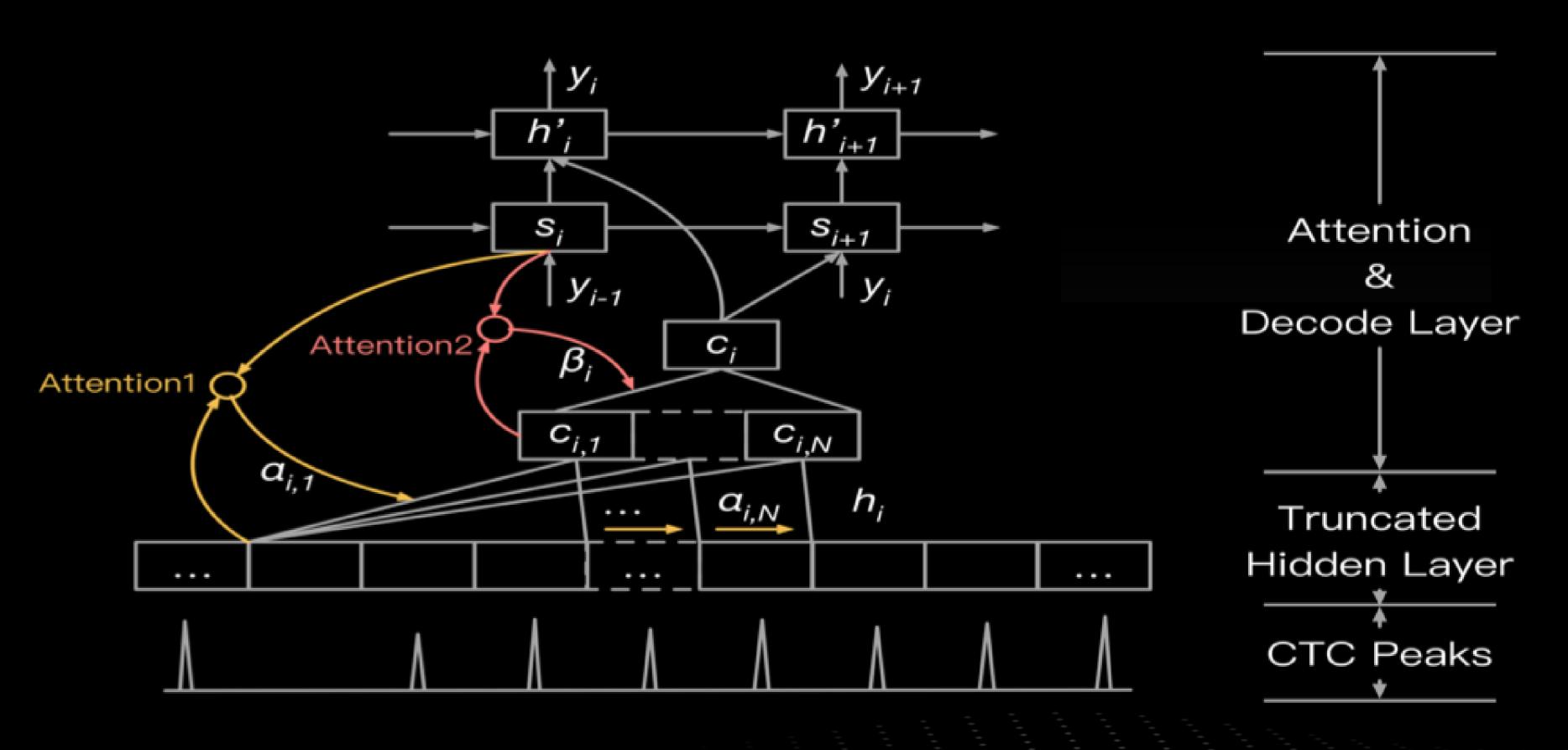


# Speech Recognition Model — SMLTA

### Features

- Streaming
- Multi-layer Neural Network
- Large Data Code Switching





Tech blog: research.baidu.com/Blog/index-view?id=109

# Text-to-Speech Synthesis (TTS)





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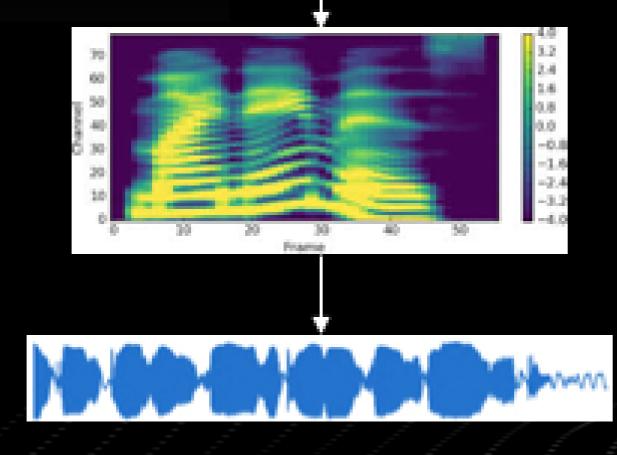
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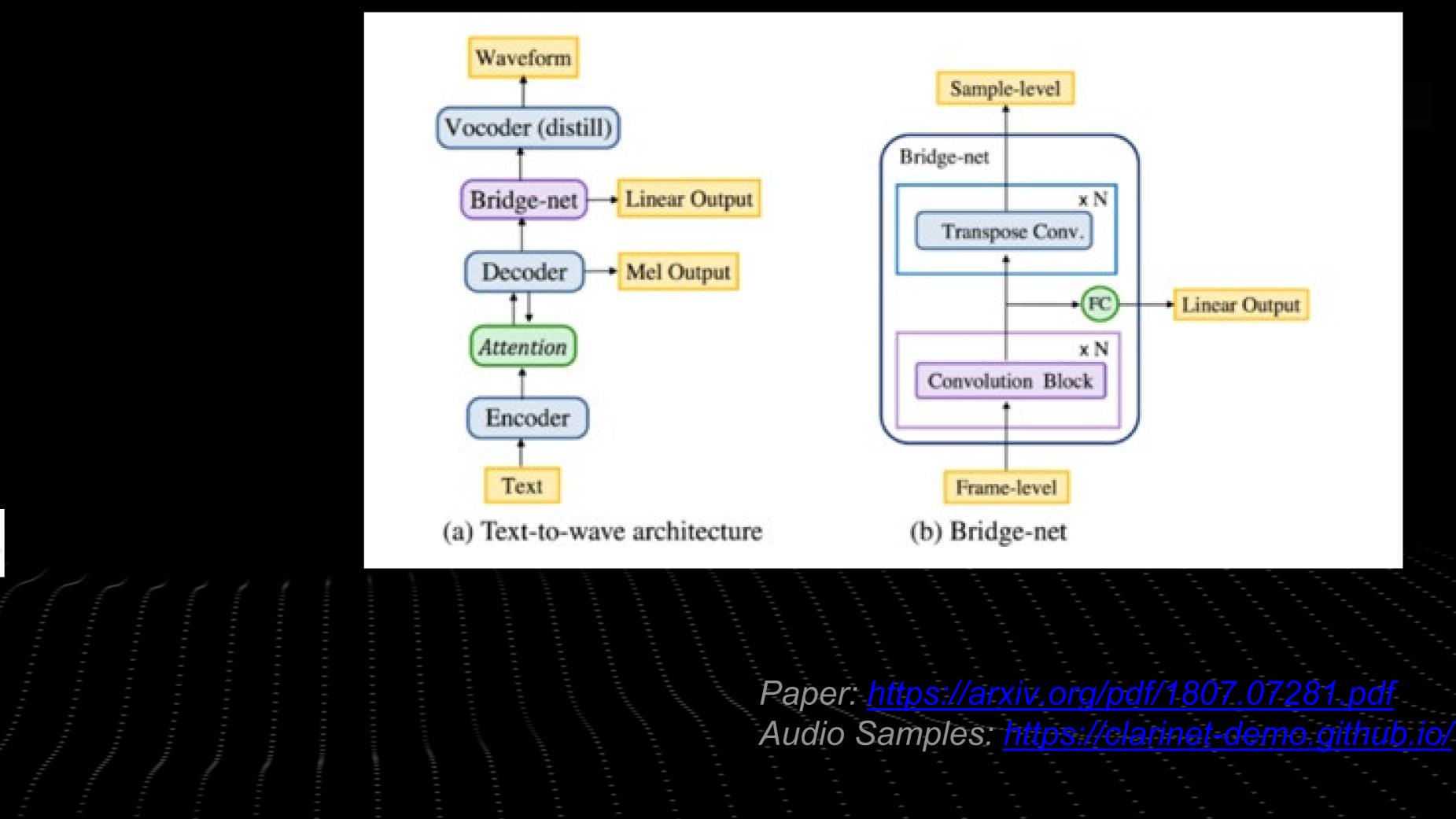
# TTS Model — Clarinet

### A Fully End-To-End Neural Network Model

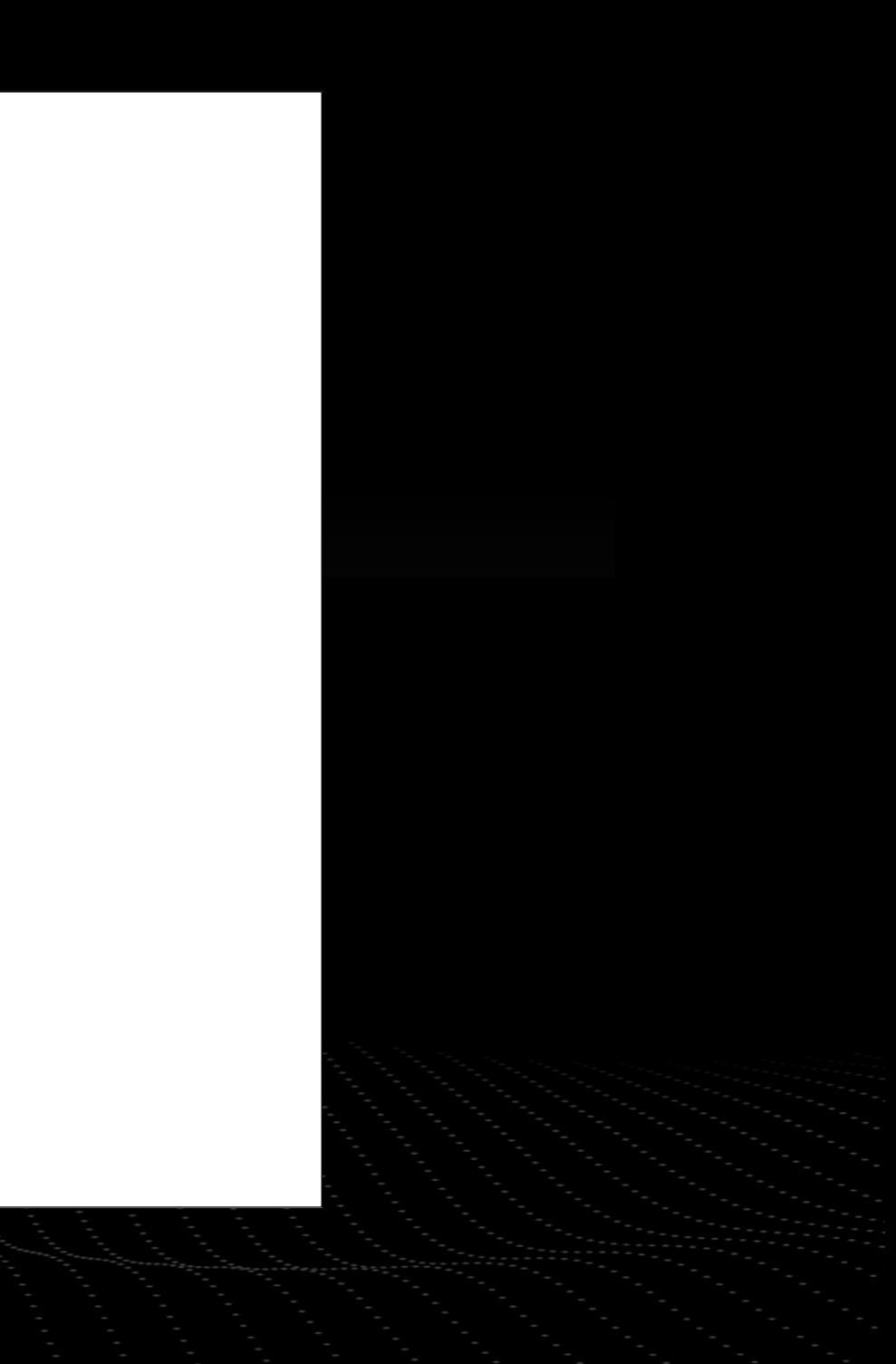
Text Phonemes



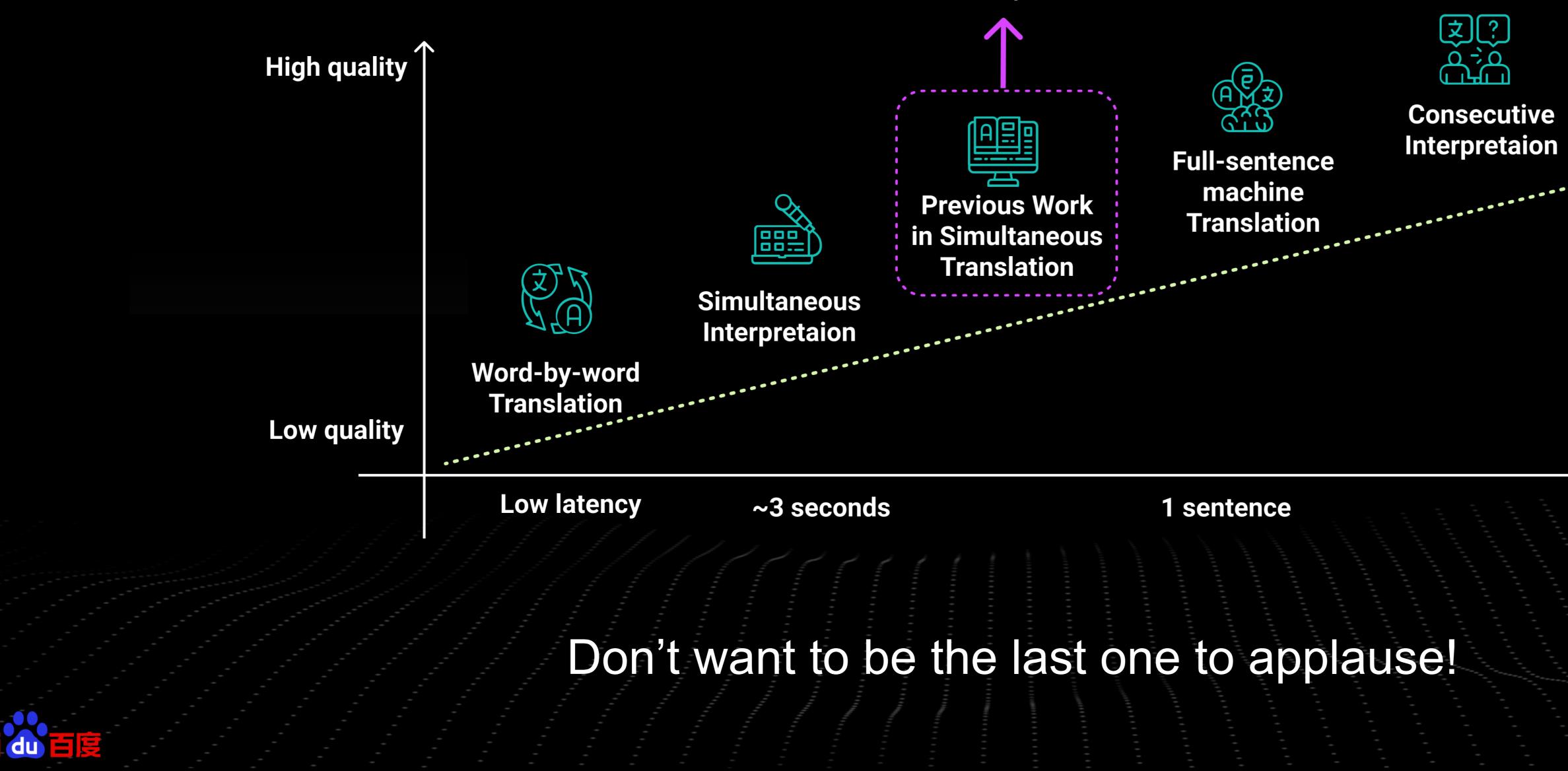






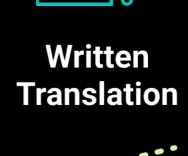


# Tradeoff between Latency and Quality



One of Al's Holy Grails Needs Fundamentally New Ideas!







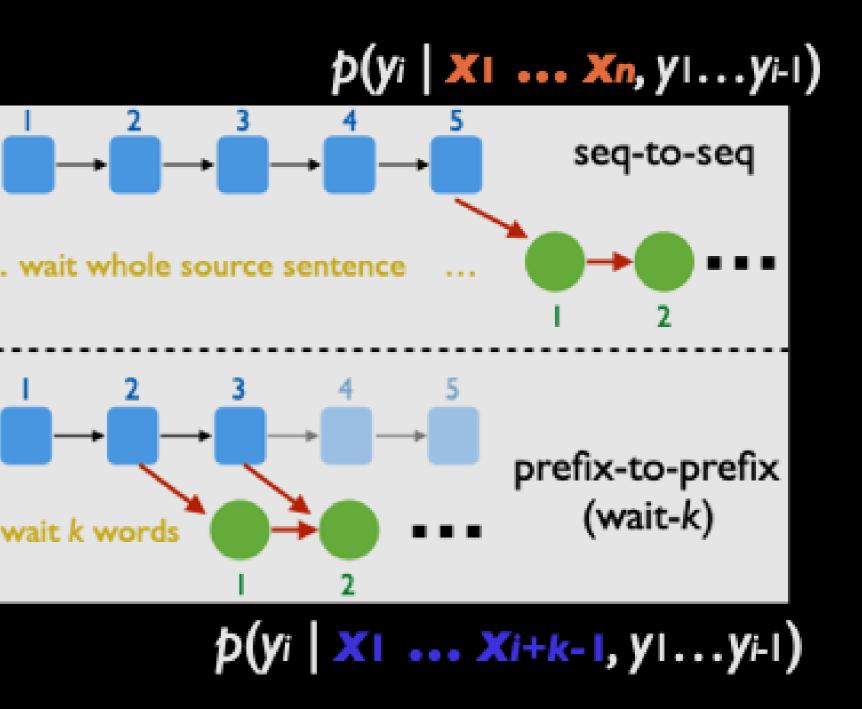
# Simultaneous Translation Model — STACL

### A prefix-to-prefix framework

Controlable latency







source:

target:

source:

target:

# Natural Language Processing

### Challenge

- NLP is a diversified field with many distinct tasks
- Shortage of training data

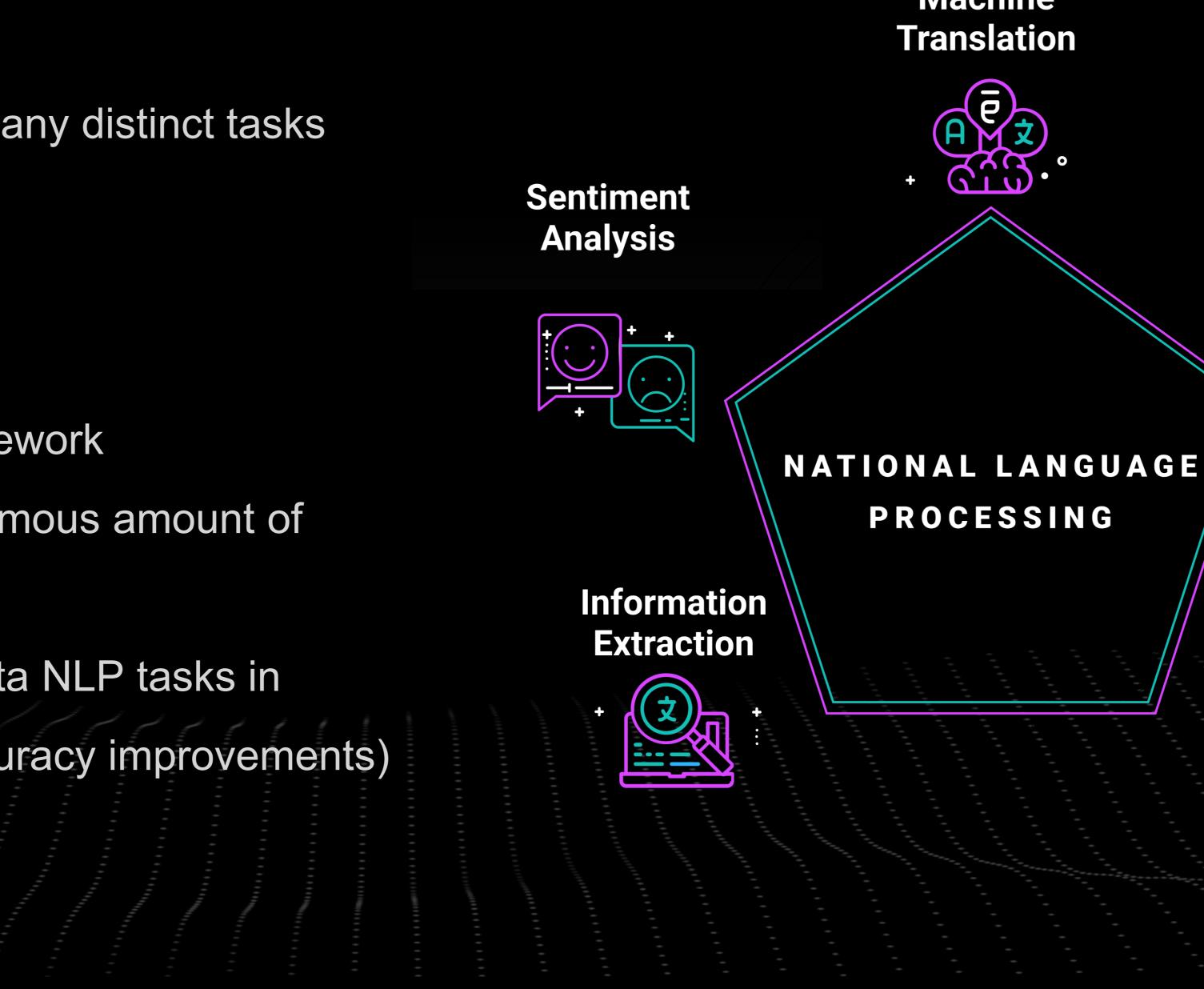
### New Trend

- Pre-training + Fine-tuning framework
  - Pre-training(using the enormous amount of

unannotated text data)

- Fine-tuning(using small-data NLP tasks in
  - resulting in substantial accuracy improvements)





### Machine

Question Answering



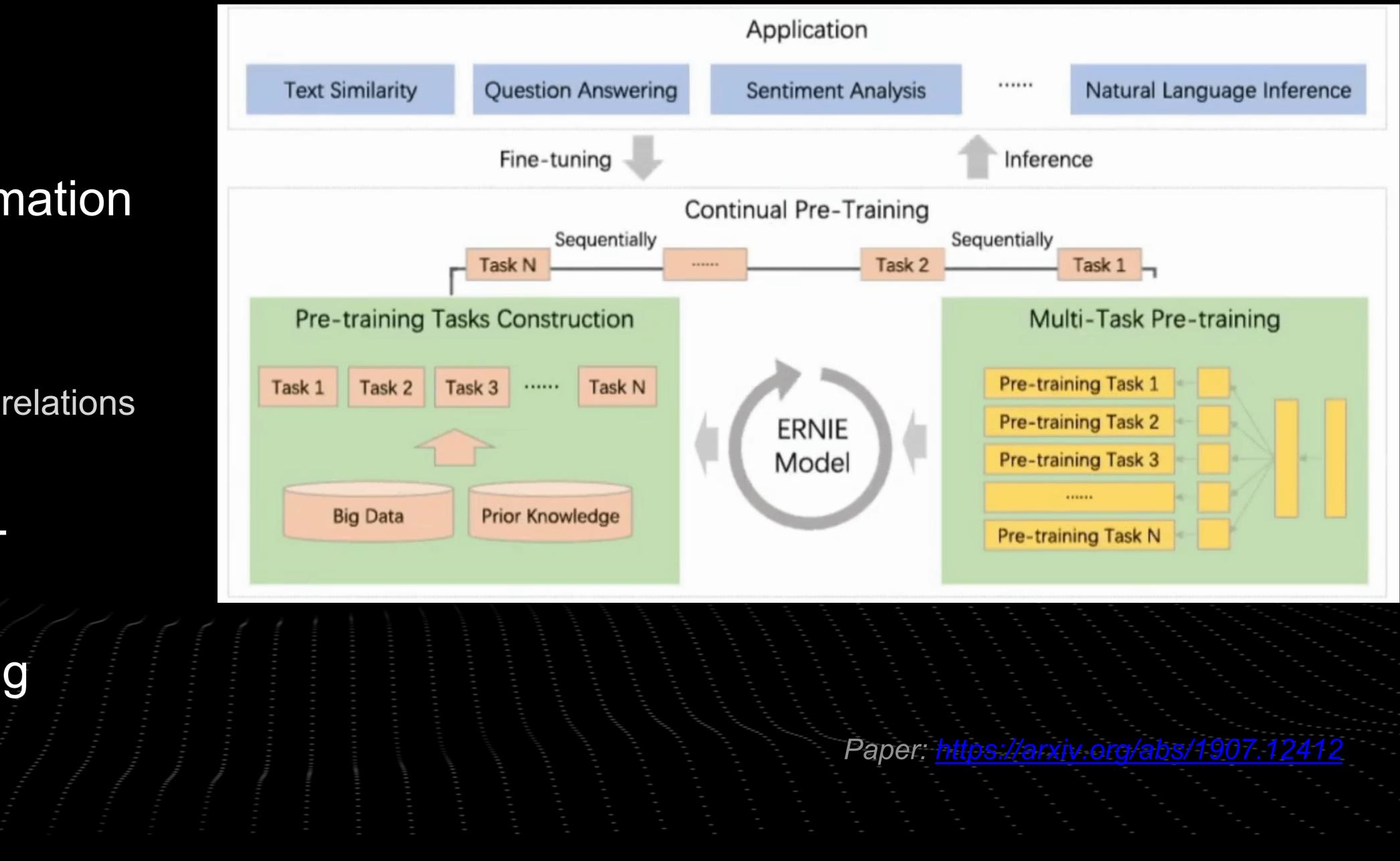
Information Retrieval



# Language Model — ERNIE 2.0

- Inspired by BERT
- Incorporate more information
  - Named entities
  - Semantic closeness
  - Sentence order or discourse relations
- Design a continual pretraining framework for language understanding





# Bigger Model is Better?

Model	Hidden size	Layer	Parameters
BERT-base	768	12	110M
BERT-large	1024	24	340M
GPT2-large	1024	24	1.5B
Megatron	1024	72	8.3B
T5	E1024 D1024	E24 D24	11B

"BERT was performed on 16 Cloud TPUs (64 TPU chips total). Each pretraining took 4 days to complete". Paper: https://arxiv.org/pdf/1810.04805.pdf

interconnect with supporting CPU host machines." Paper :<u>https://arxiv.org/pdf/1910.10683.pdf</u>.

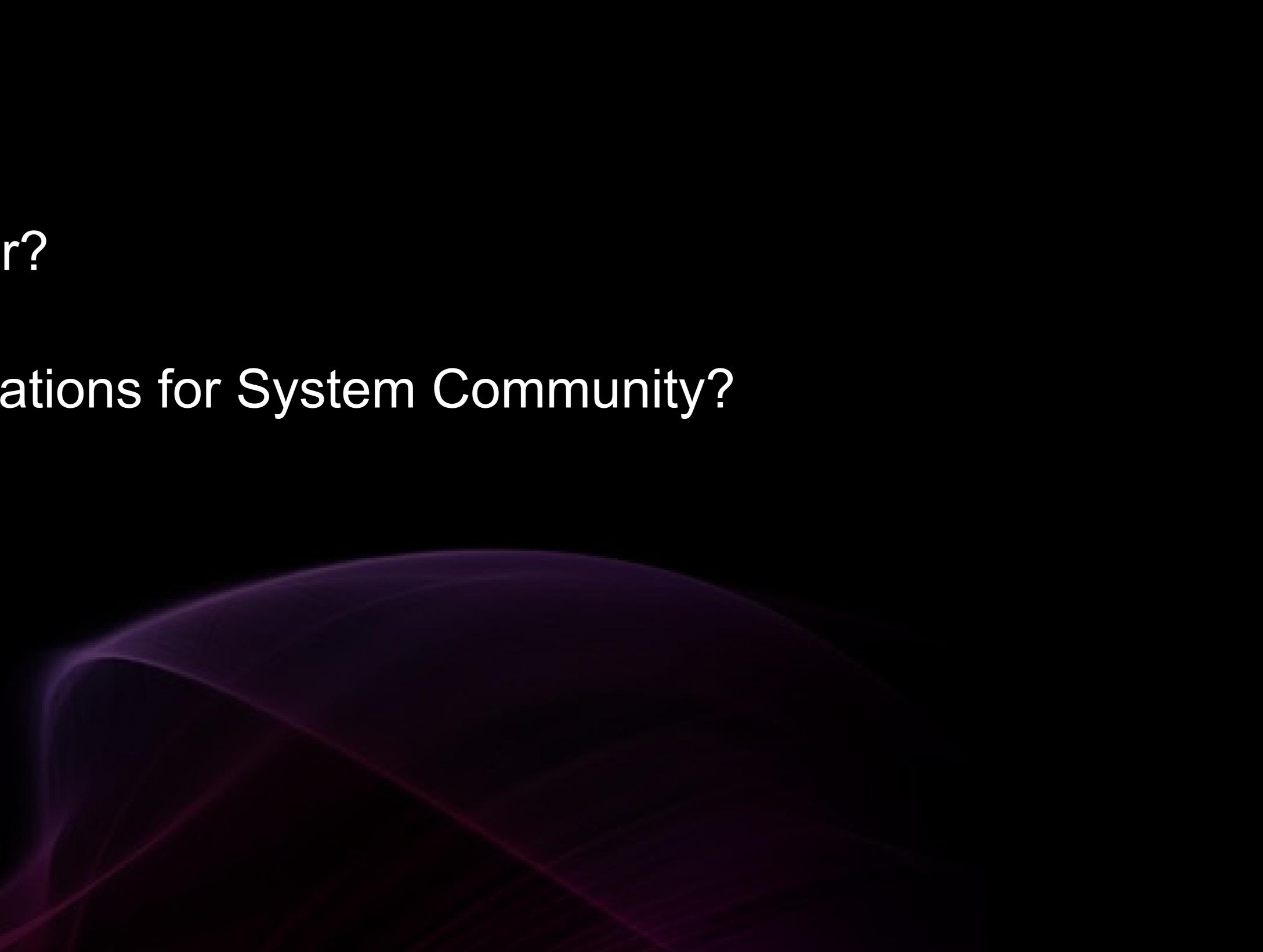




## Why Bigger is Better?

### What Are the Implications for System Community?





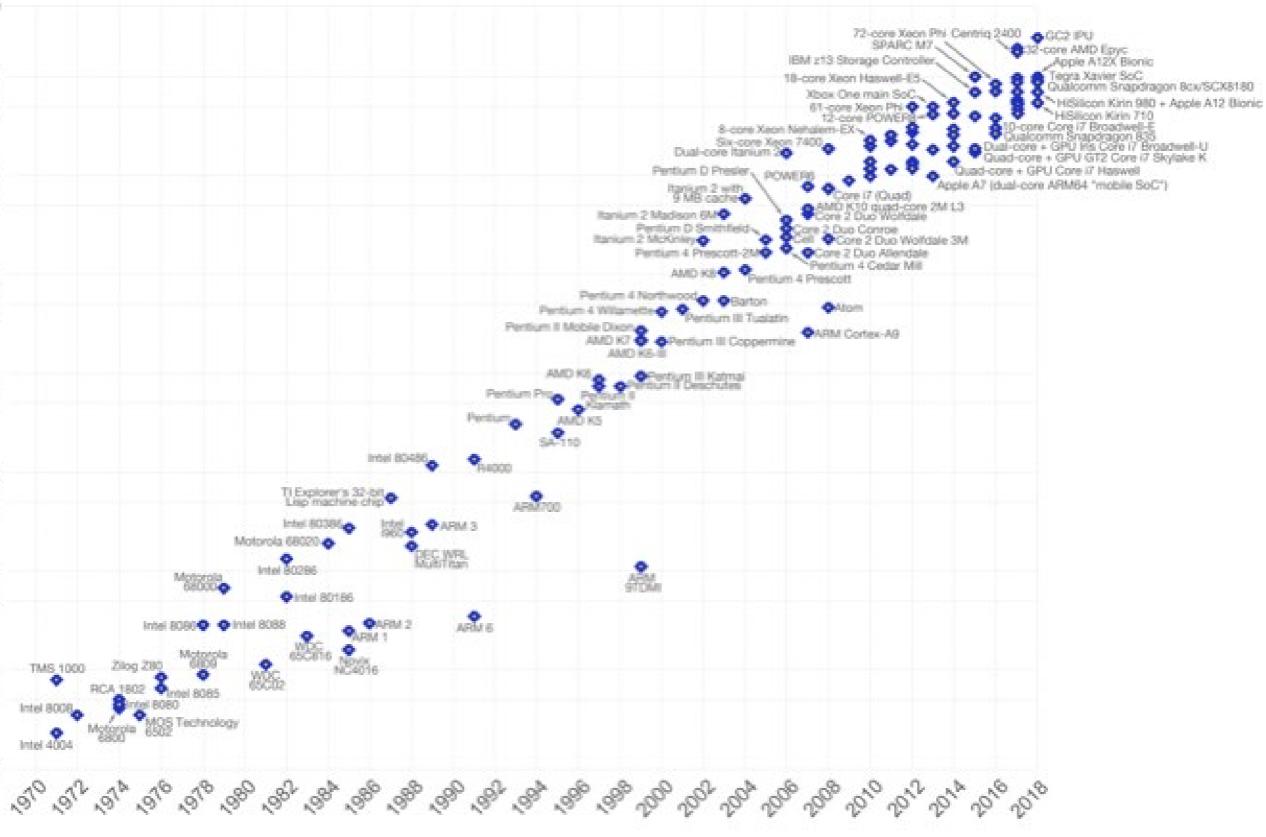
# Moore's Law

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10	0,000,000,00
5	5,000,000,00
1	,000,000,00
	500,000,00
	100,000,00
count	50,000,00
tor	10,000,00
ransis	5,000,00
-	1,000,00
	500,00
	100,00
	50,00
	10,00
	5,00
	1,00



### aw – The number of transistors on integrated circuit chips (1971-2018)

ribes the empirical regularity that the number of transistors on integrated circuits doubles approximately every two years. It is important as other aspects of technological progress – such as processing speed or the price of electronic products – are law.

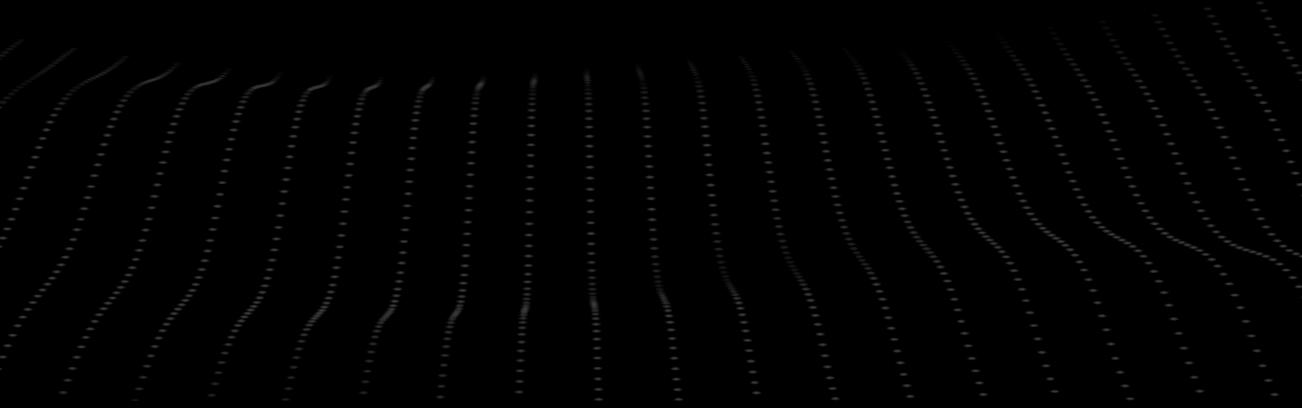


Data source: Wikipedia (https://en.wikipedia.org/wiki/Transistor\_count)

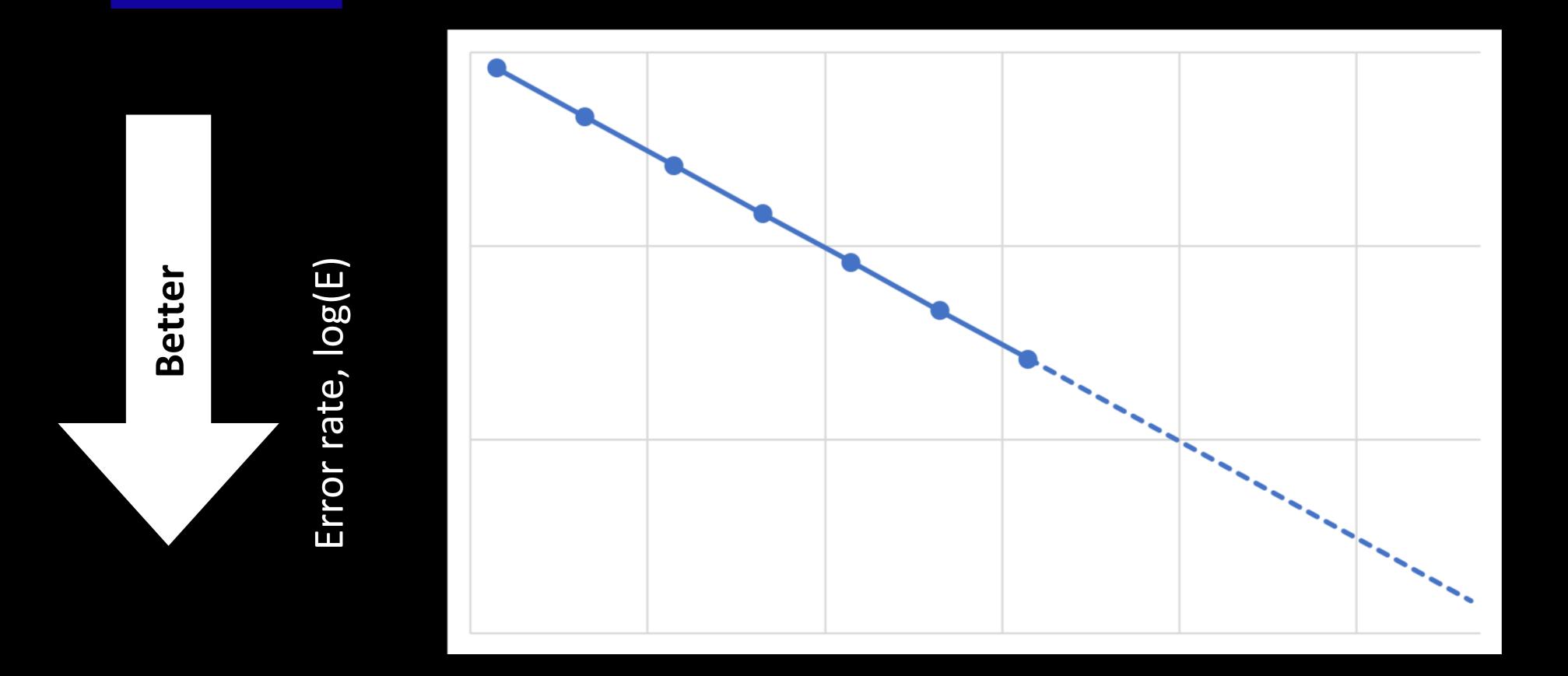
# What does it mean to be "Better"?

# Better Accuracy Faster Training





# Better as Better Accuracy



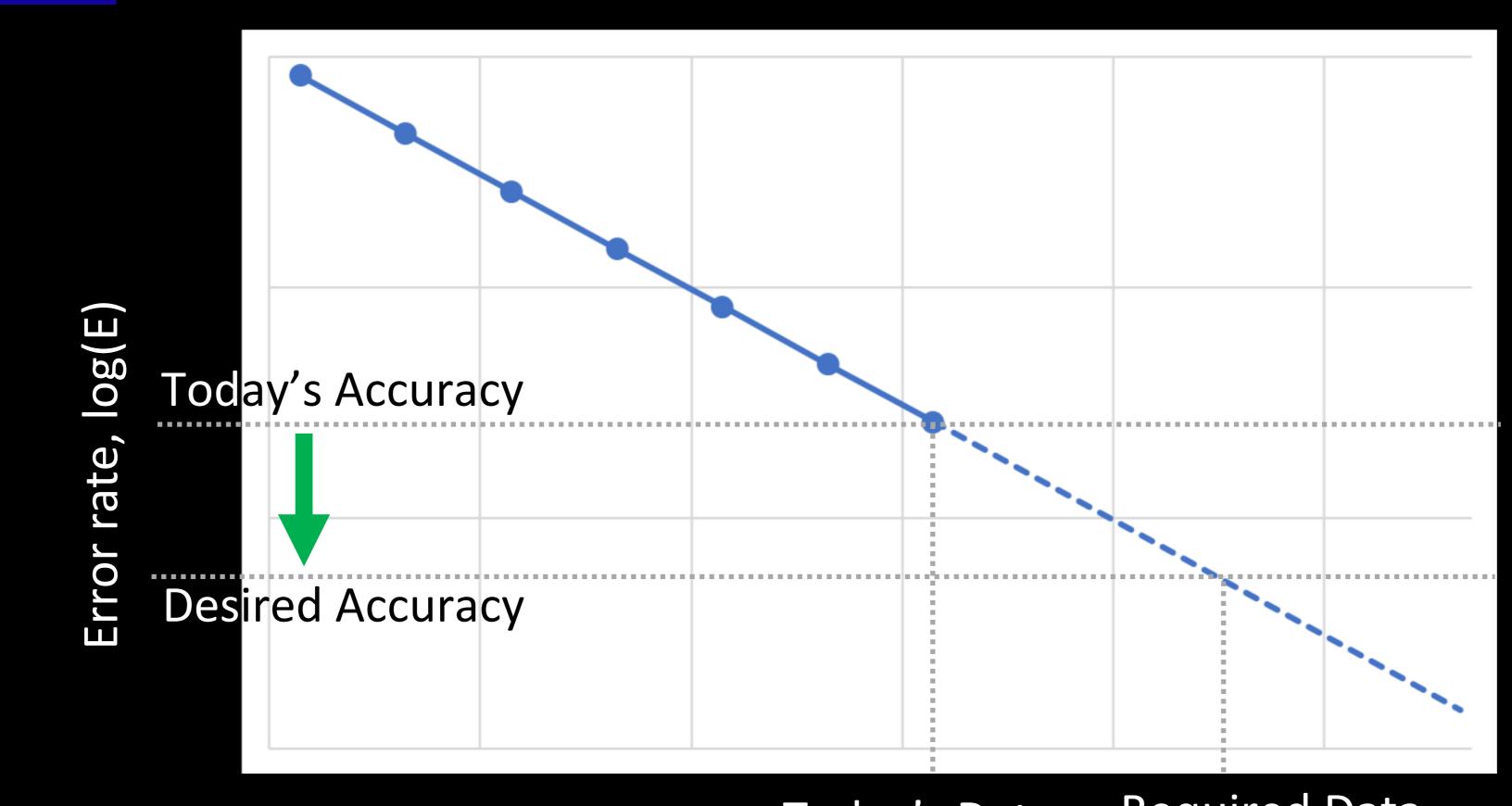


### # training samples, log(d)

Bigger

Hestness, J., Narang, S., Ardalani, N., Diamos, G., Jun, H., Kianinejad, H., ... & Zhou, Y. (2017). <u>Deep learning scaling is predictable, empirically.</u> arXiv preprint arXiv:1712.00409.

# Better as Better Accuracy

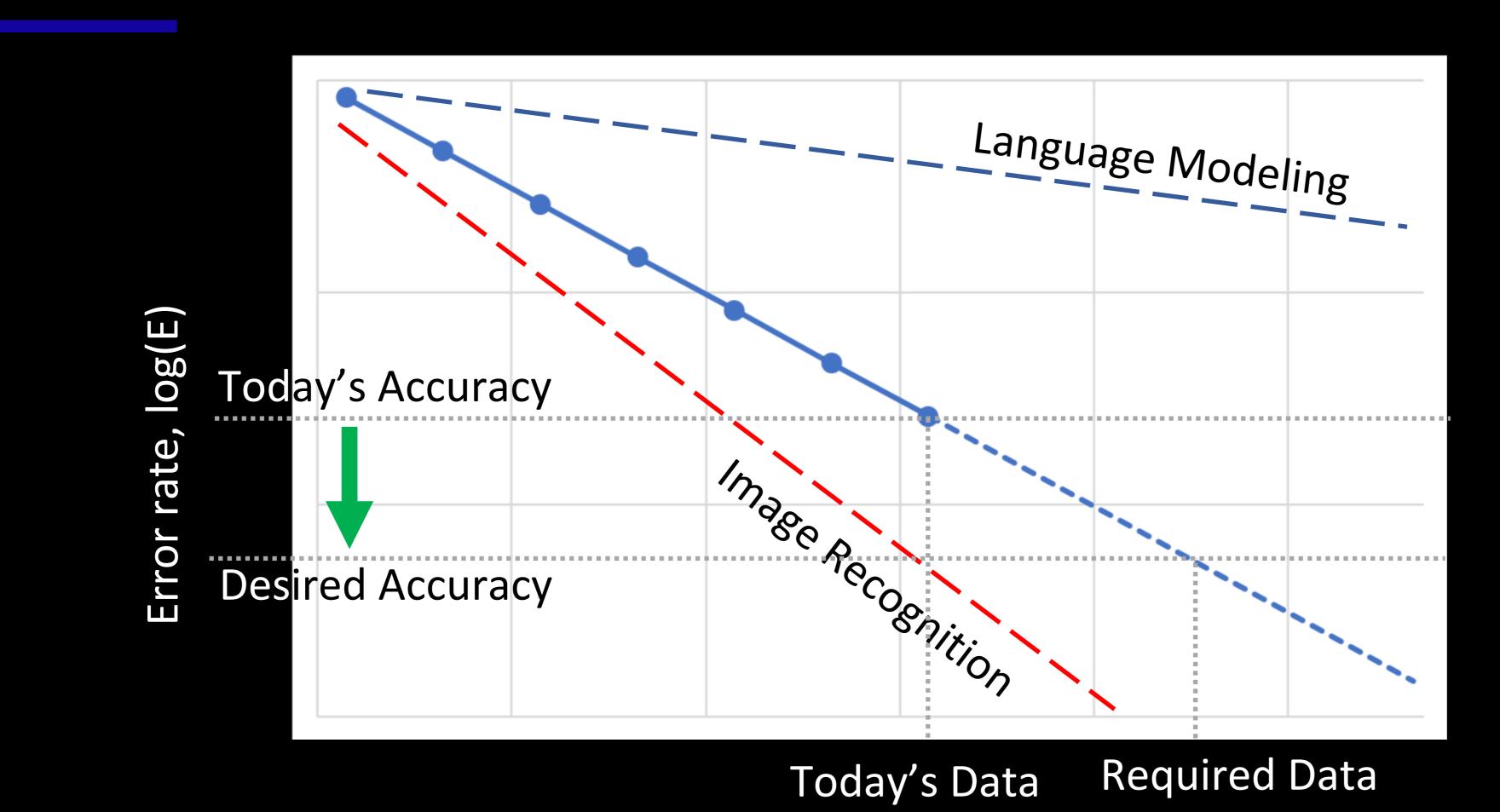




Today's Data Required Data # training samples, log(d)

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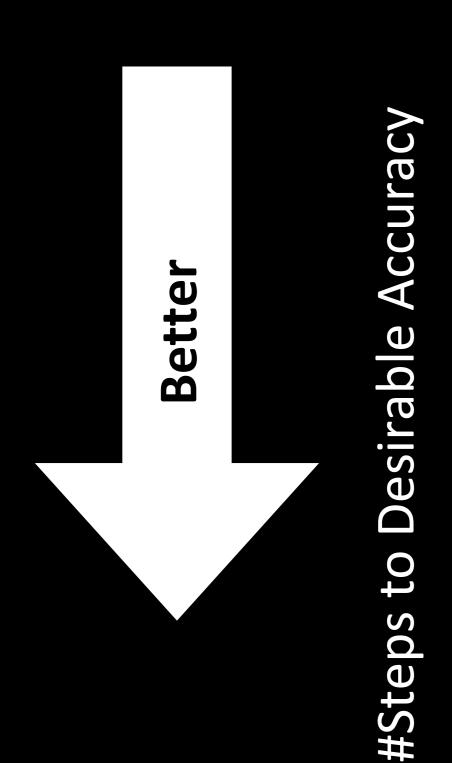


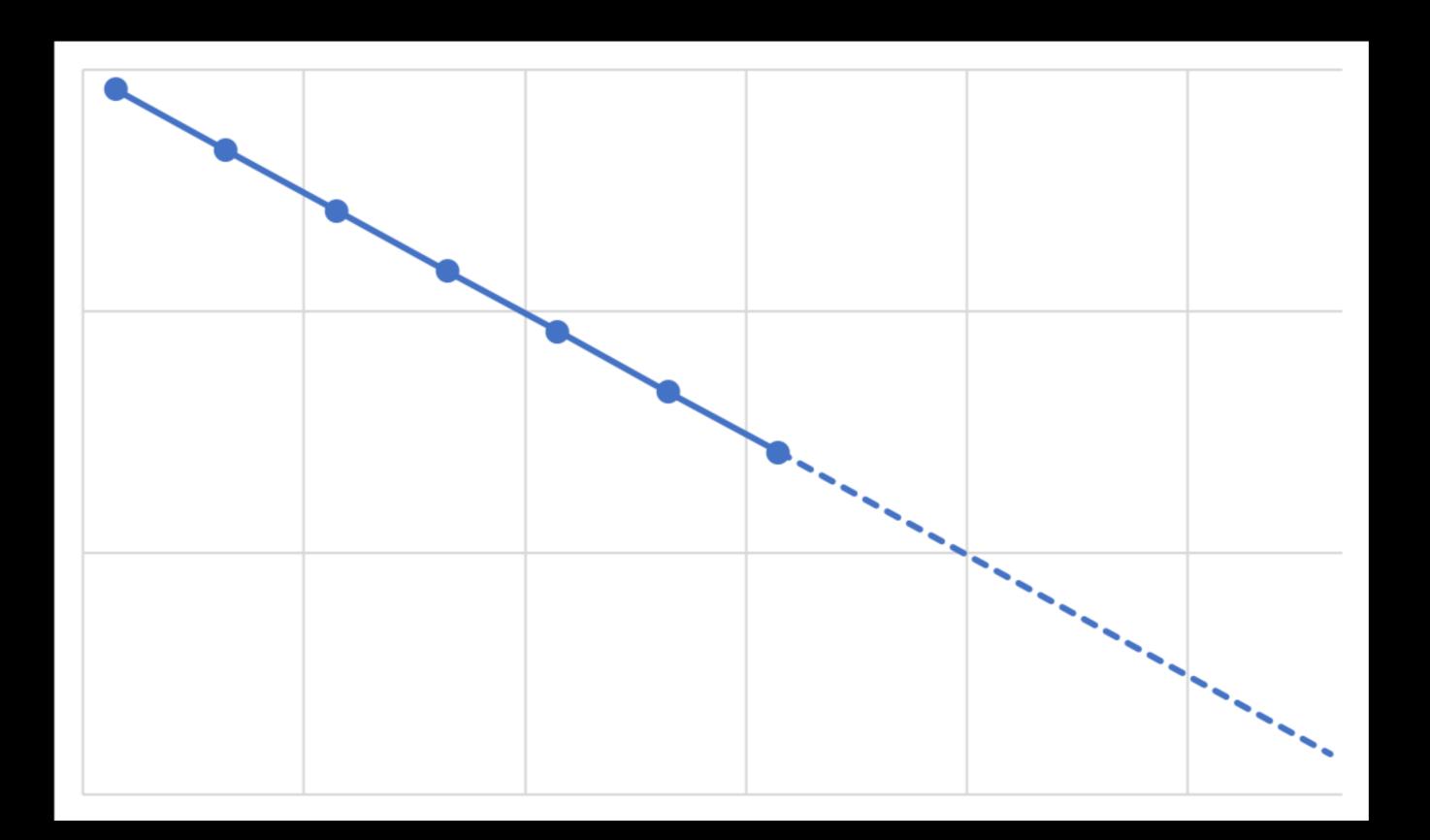


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# Better as Faster Training



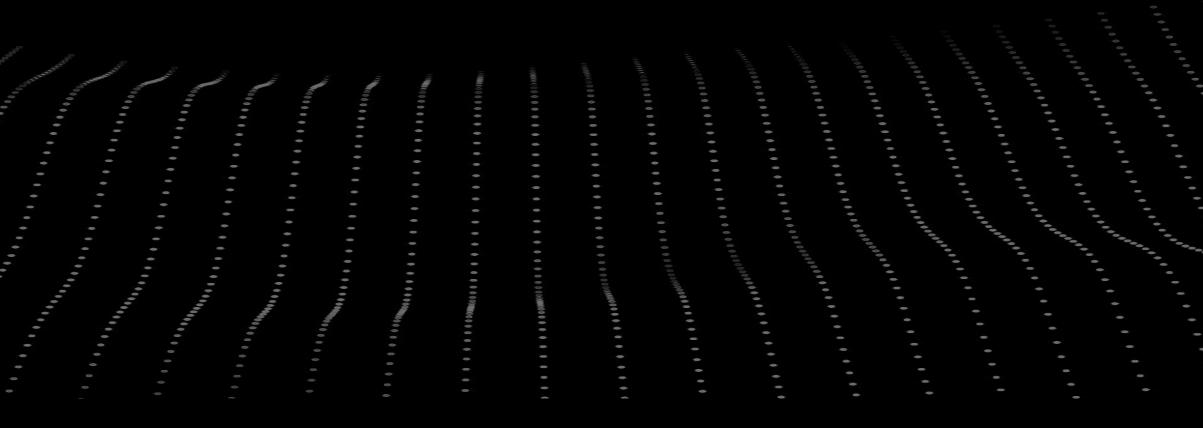




#Parameters, log(m) Bigger

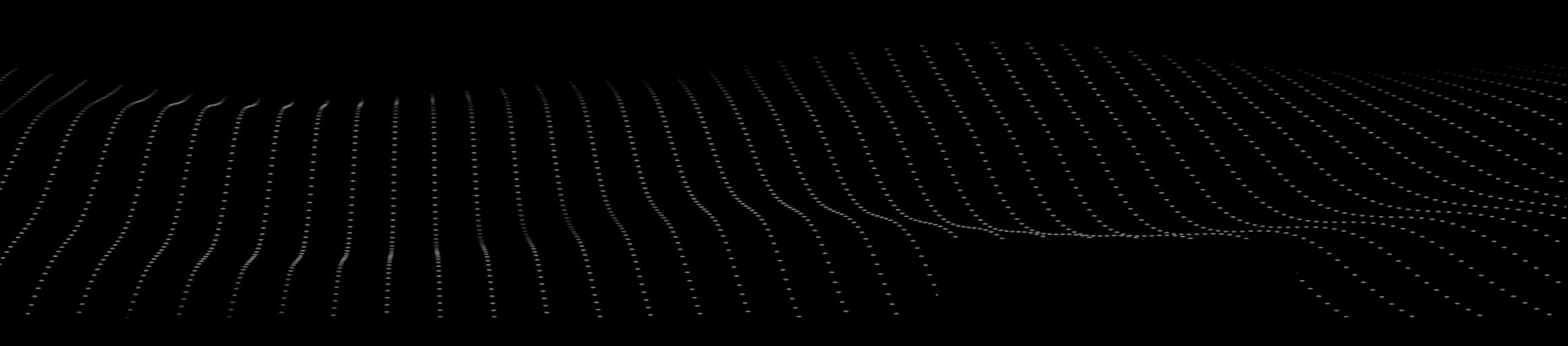
Ardalani, N., Hestness, J., and Gregory Diamos. "Have a larger cake and eat it faster too: A guideline to train larger models faster." (SysML 2018).





### Memory capacity/chip can grow only so much...

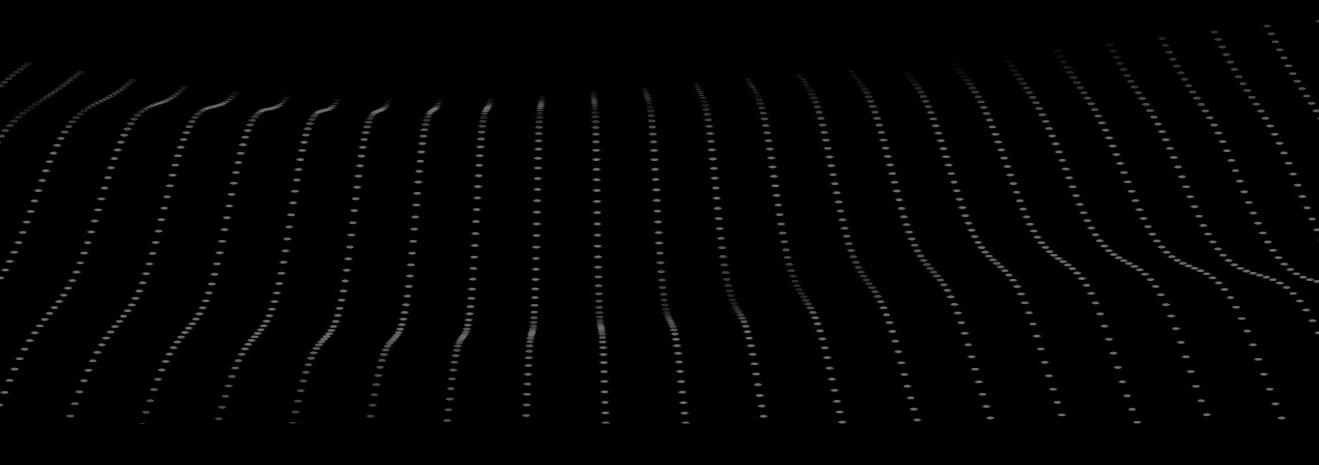




### Memory capacity/chip can grow only so much...

### Break the model and data into smaller chunks



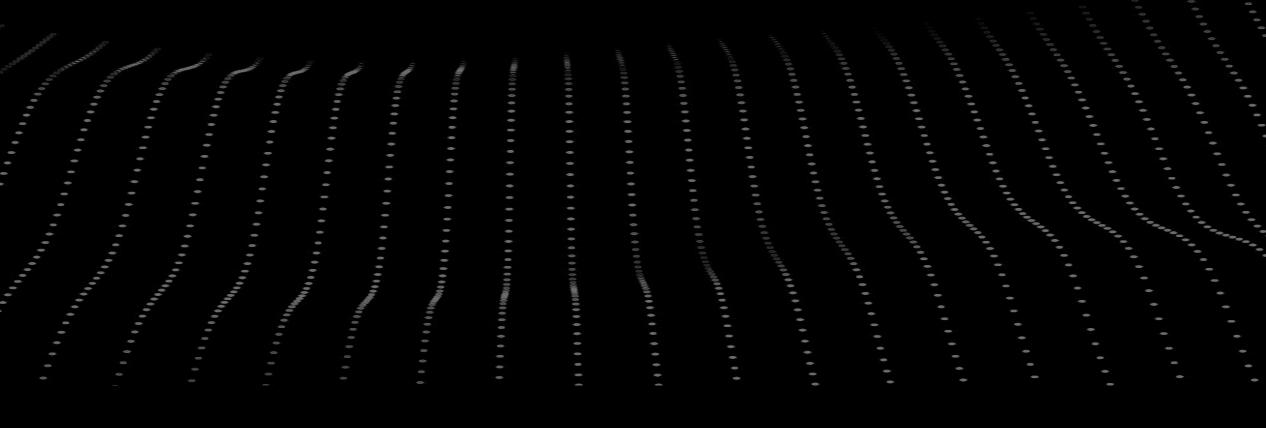


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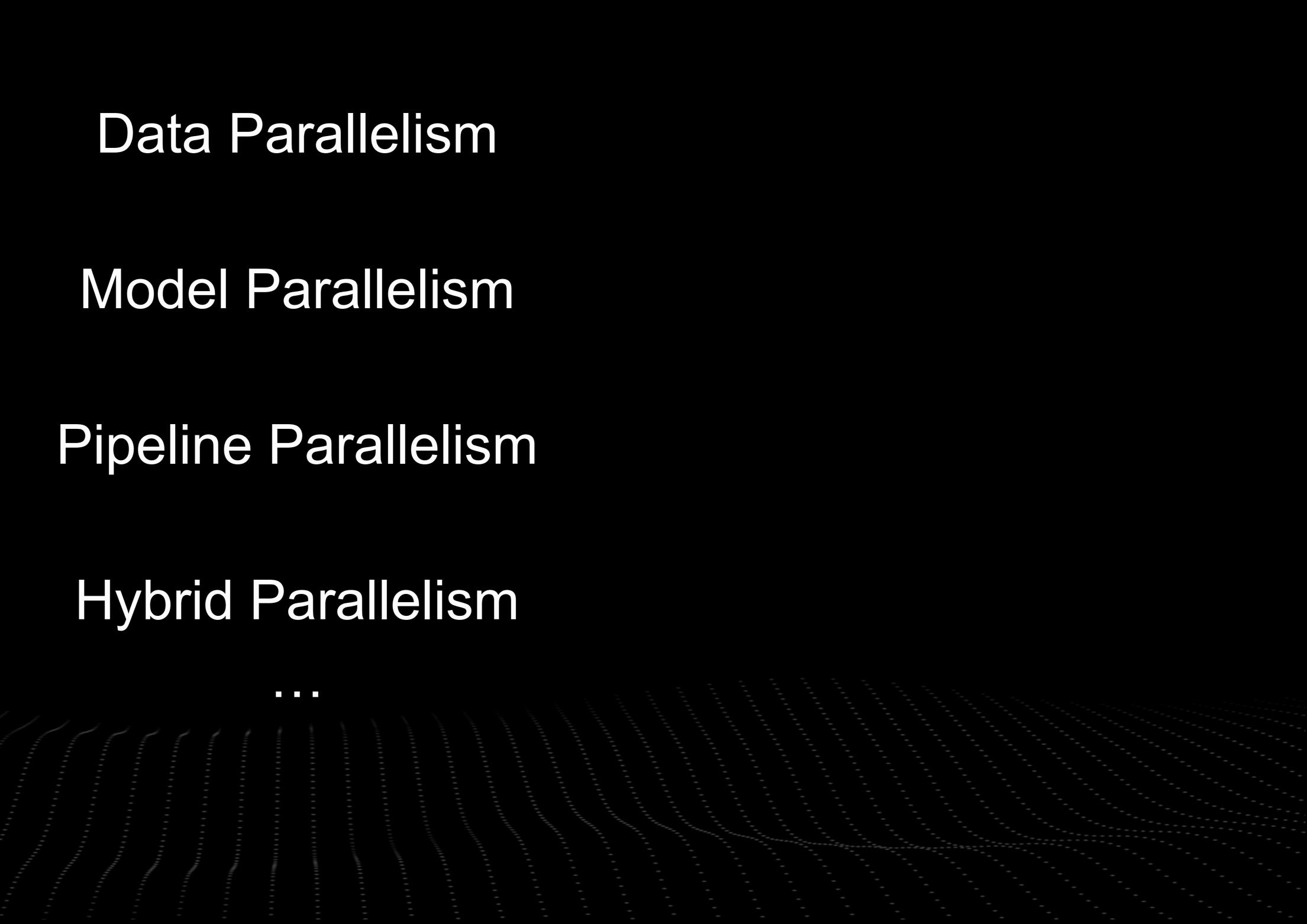
### We need to exploit all forms of parallelism



Memory capacity/chip can grow only so much...







### Current Practice: Hire Expert Programmers



# How to find a good parallelism strategy?

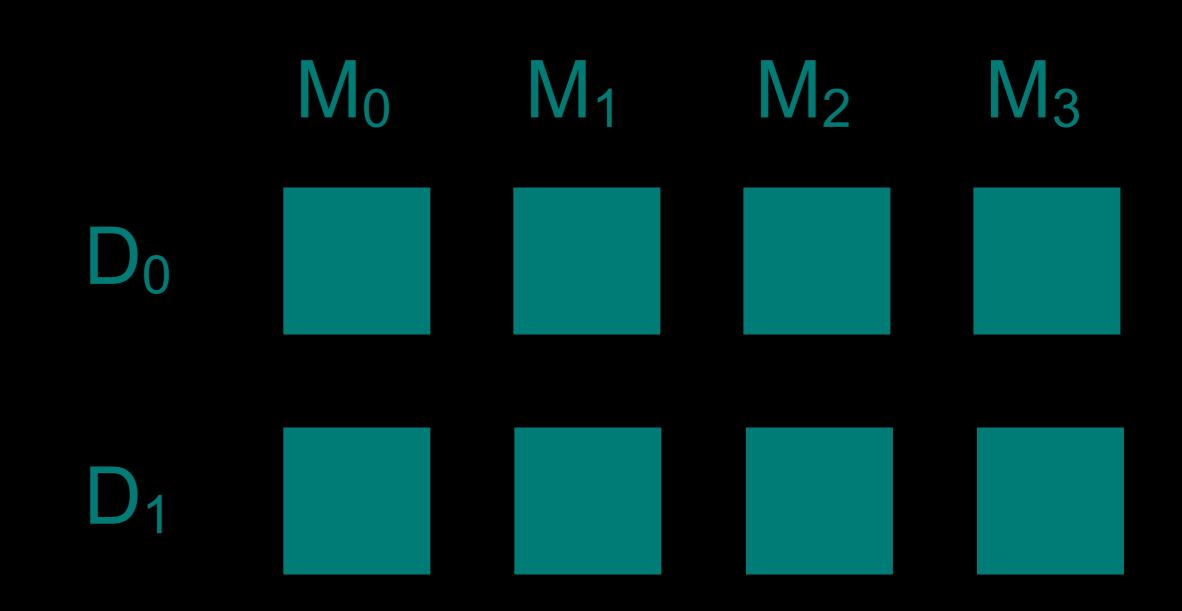
 $M_0$ 

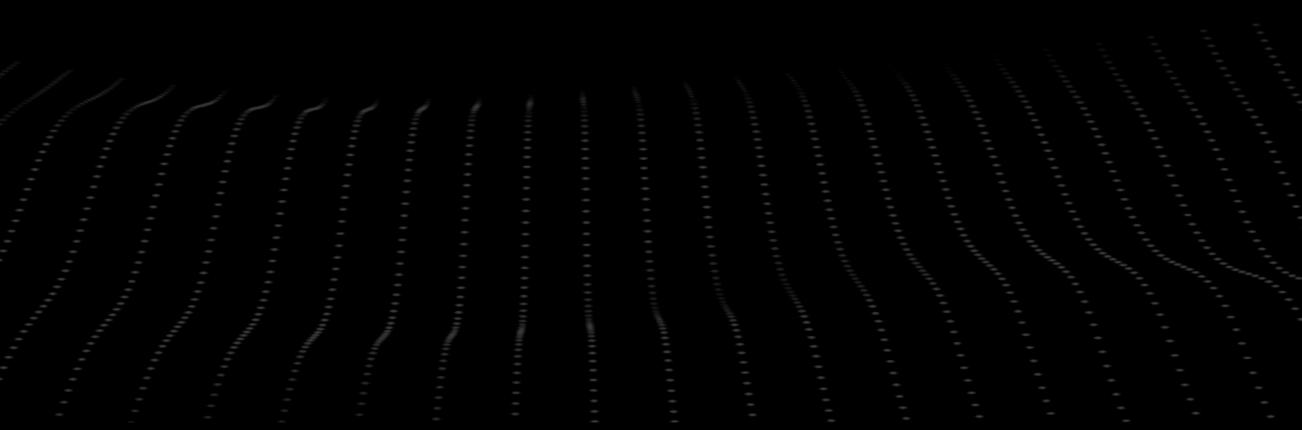
# $M_1$ $M_2$ $M_3$

### **Current Practice: Hire Expert** Programmers



# How to find a good parallelism strategy?

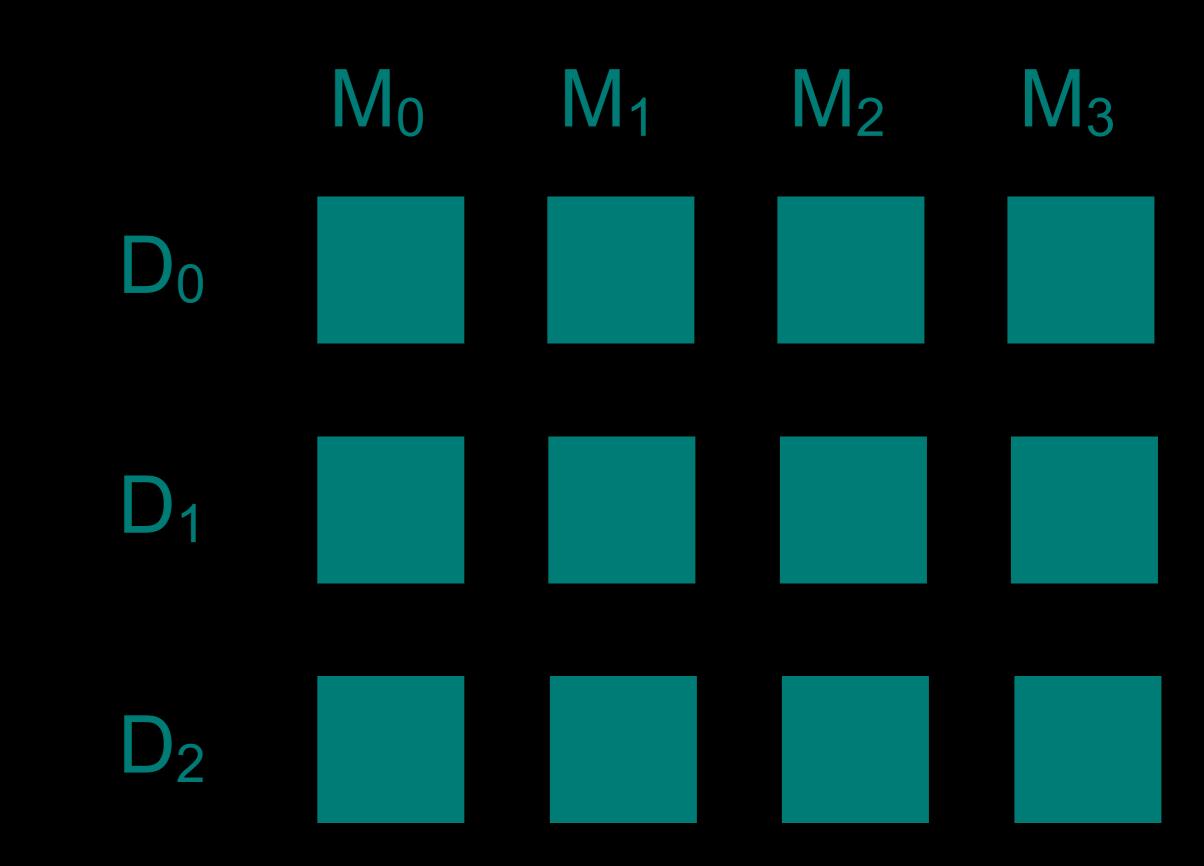


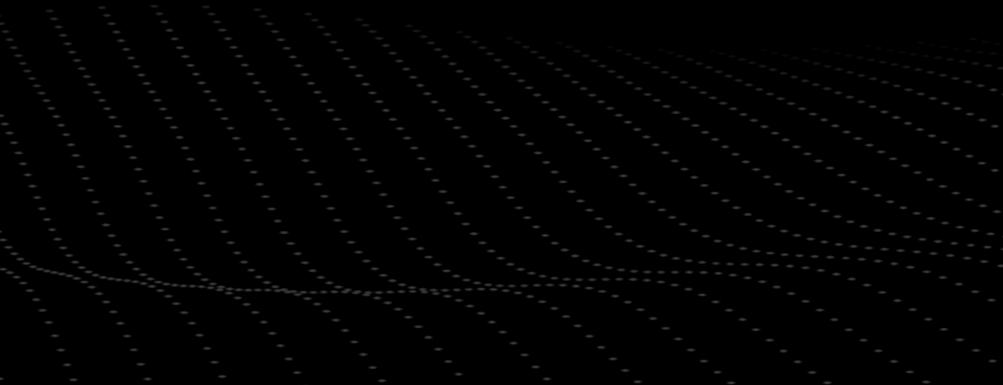


### Current Practice: Hire Expert Programmers



# How to find a good parallelism strategy?



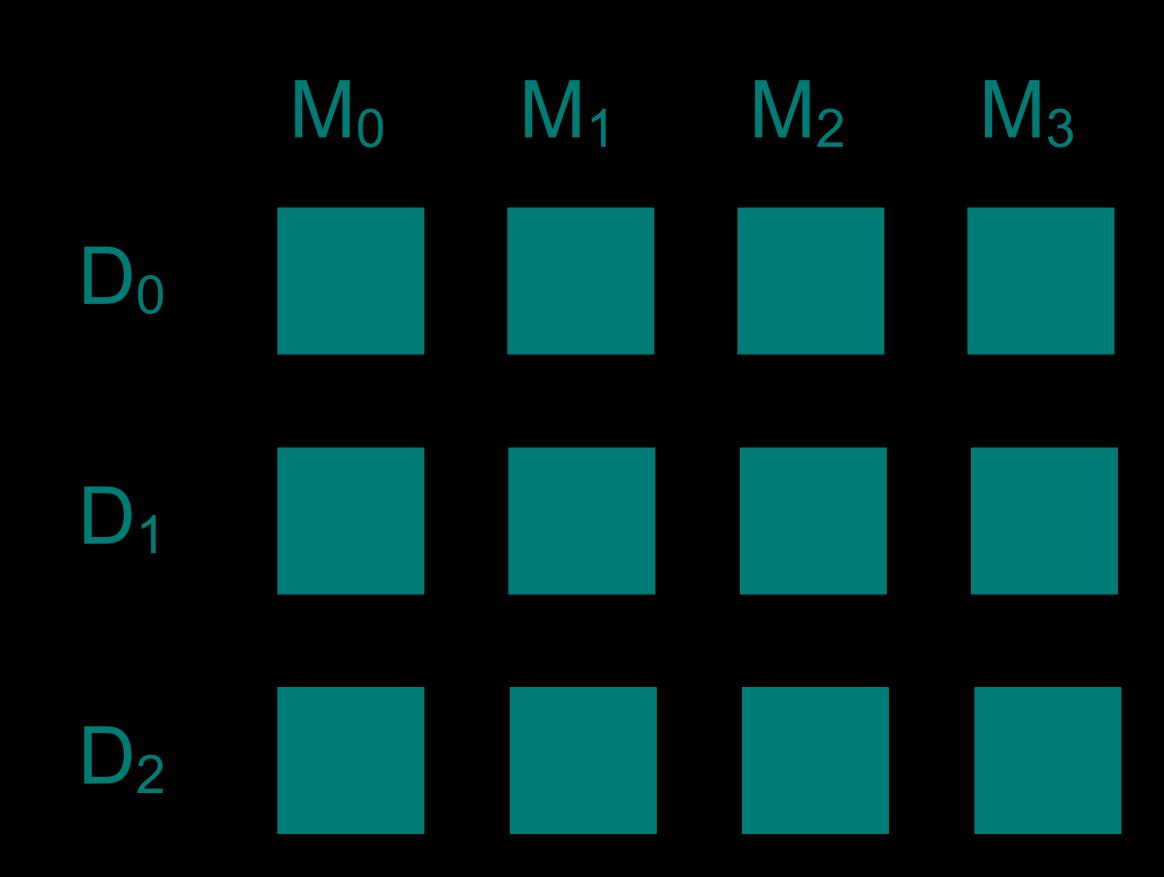


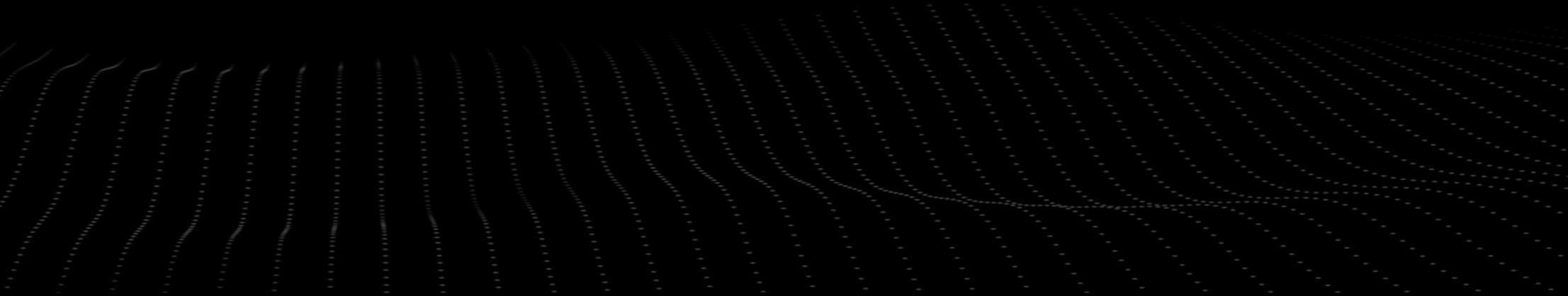
# How to find a good parallelism strategy?

- **Current Practice: Hire Expert** Programmers
- Cutting edge: Reinforcement Learning, Dynamic Programming





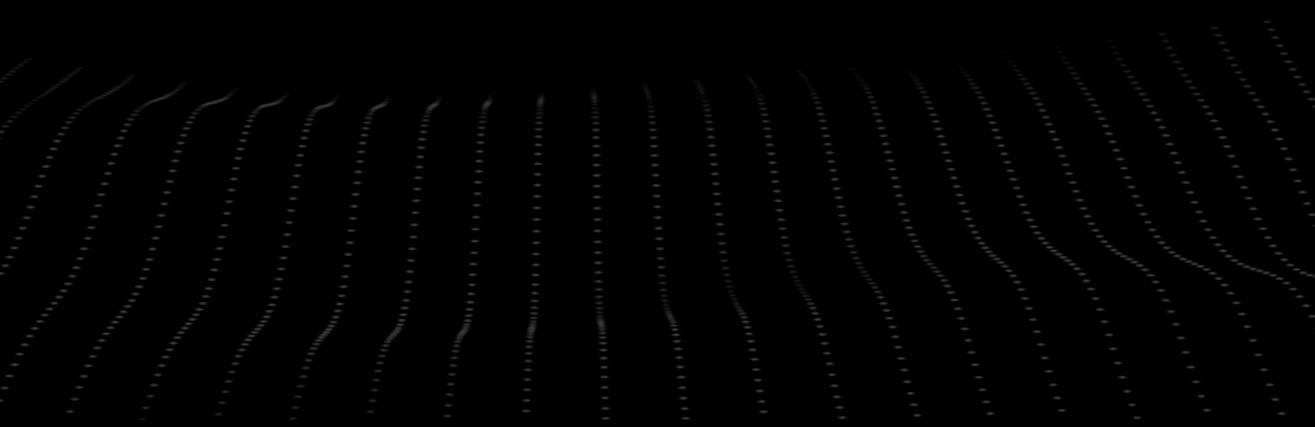




# GOOD NEWS Best mapping/Best timing



## BAD NEWS System Under-utization



# Solution?

# Co-design Parallelism Strategy & Hardware Accelerator





# Conclusion

### GOOD NEWS Bigger is Better



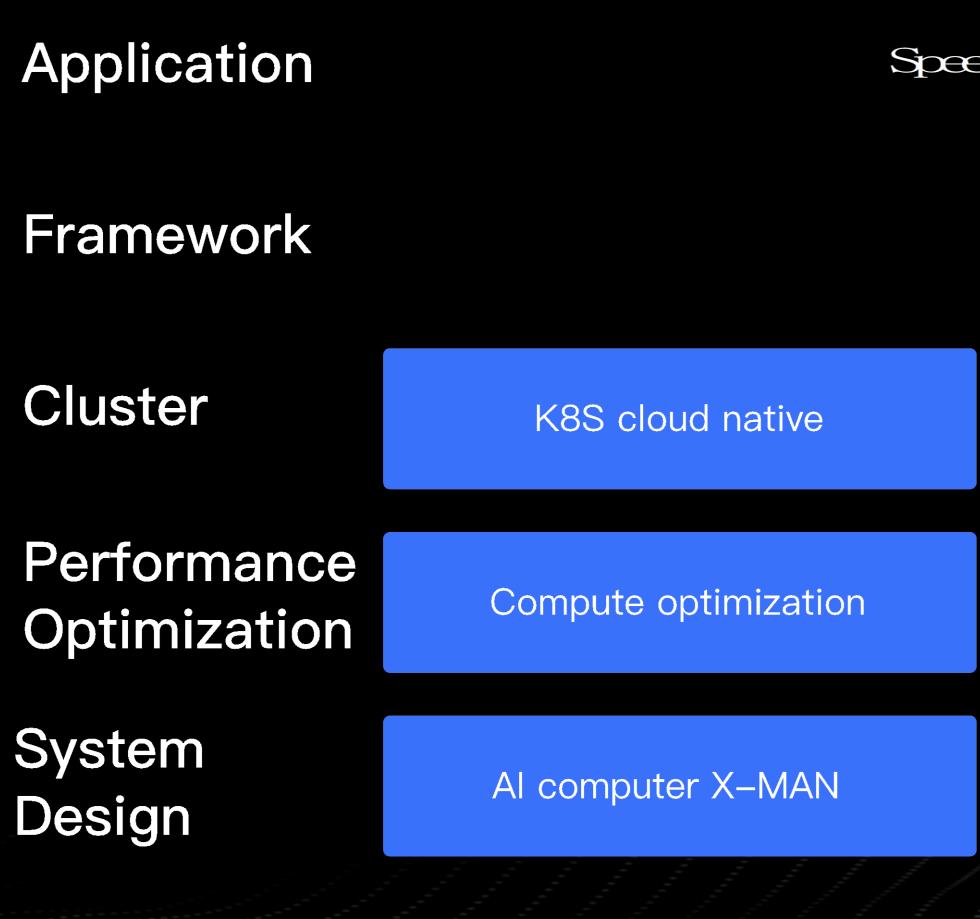
# Memory is Bottleneck Systems Underutilization

### WHAT CAN WE DO?



# **Cloud AI Computing Platform KongMing Architecture**

GPU



Chip

CPU



Speech/Inages/NLP/Recommendation

PaddlePaddle

Smart Scheduling

IO optimiaztion

Elastic provision

Communication optimzation

High performance storage pool

High speed interconnect

ASIC

Baidu Kunlun







