Beyond transformers: Mixture of Expert Models
What makes a good researcher?

- Top 1% of researcher produce 20% of all citations
- Accumulated advantage the most important factor that creates good researchers
- How Nobel Laureates are made (according to Harriet Zuckerman):
  - Nobel Laureates start out not better than any other researcher
  - They gain a small advantage through chance or luck
  - That advantage gives them more resources and opportunities ("better" university, more grants, more students, awards, more lab resources, more GPUs)
  - Once they receive the advantage, it's easier to gain more advantage
  - Repeat ... repeat ... repeat ...
  - Nobel Laureate
- By this point, Nobel Laureates are better researcher, mostly due to research style learned from their advisor and research group
What makes a good scientist? Research style!

- Good science is good math. A paper should be mathematically solid so that it will stand for years, holding valuable insights and generalizations that go beyond the current theoretical application.
- Good science is robust science. A paper should have careful claims with robust evidence. This will help make the field progress more quickly by providing reliable information to build on.
- Good science is a good research vision. A paper should be about what is possible in the future and where a line of research could lead to. Evidence augments vision, but a paper without vision is blind, incremental, and will be forgotten.
- Good science is good insight. Some insights can be extrapolated and be applied to many other scientific problems, many of which have not been formulated yet. Finding and expressing these insights is vital for scientific progress.
- It is all about productivity. Research is inherently noisy and messy, and it’s tough to predict the outcome of an idea or set of experiments in the development stage. Navigating this uncertainty is best done through fast iterations and balancing multiple projects to maximize the chances of a big success.
- Good science is collaborative. Different people can bring unique perspectives to a project and increase the chance of serendipitous insights. Collaborations bring the best out of people and can result in a sum that is larger than its parts.
- Good science is solitary. To gain the deepest insights into a problem, one has to understand a problem in its fullness without outside help. While collaborators provide perspectives and feedback, they cannot replace the depth of understanding that comes from insight.
This lecture is about following a particular research style

You will learn in this lecture about mixture of experts, but that is not the main lesson.

The main lesson is to follow the research style of “computational efficiency is everything” to its conclusion.
Our tenet for this lecture

**Intelligence = \min(\text{Compute/waste, data movement/waste})**

**Important:**
- Balance computation and data movement (communication)
- Maximize computation and data movement to create the most intelligence
- Reduce waste to a minimum: Every computation and data movement needs to be needed

**Not important:**
- Anything that has not to do with these variables
This is naive in many ways. It is a hypothetical view

- Each research style or view has different believes
- Believes often do not rely on good evidence or have some weak points
- Opposite research styles might be successful
- Some research styles are only successful for a while to focus on a particular problem
Why the computational perspective could make sense

1. Intelligence roughly proportional to number of cortical neurons (compute):
   a. Humans 10x more neurons than Chimpanzee/Dolphins/Crows/Elephants
   b. Chimpanzees 10x more neurons than dogs
   c. Dogs 2x more neurons than cats
   d. Cats 50x more neurons than bees
   e. GPT-3 roughly as much compute as a bee

2. Primate brains are special. They are optimized for data movement (sparsity)
4. Communication (white matter) and computation (grey matter) mathematically perfectly balanced across all primates (no waste)
5. Number of neurons determined by maximum energy intake across all mammals (no waste)
Primates scale differently … and so do transformers

What scales better than transformers? Mixture of Experts

Background
In this section you will learn what limits us: compute/data movement, are we too wasteful?

What is the main problem, computation or data movement?

Why are GPUs fast?

How to do a fast matrix multiplication that balances compute and data movement?

How do we scale efficiently?

What are language models and how do they work?

What are transformers and how do they work?
Communication (data movement) much more limiting than computation

When We Look at Performance in Numerical Computations...

- Data movement has a big impact
- Performance comes from balancing floating point execution (Flops/sec) with memory->CPU transfer rate (Words/sec)
  - “Best” balance would be 1 flop per word transferred
- Today’s systems are close to 100 flops/sec per word transferred
  - Imbalanced:
    Over provisioned for Flops
How GPUs overcome data limitations, and why they are fast

Task: pick up data (packages) from location A (main memory).

Packages go from A (GPU memory) to B (GPU core). The core has a loading dock (cache) that is for packages that just arrived. Its small and cannot hold many packages at once.

CPUs are like Ferraris, super fast, but can only hold a few packages

GPUs are like trucks, super slow, but can hold lots of packages

What is more efficient for package delivery, a fleet of Ferraris or a fleet of trucks?
Most efficient to divide a matrix multiplication into smaller sub-matrix multiplications.

How to do matmul efficiently with three trucks:

1. Truck A, B, and C drive to core.
2. Truck A and B unload packages (A1, A2) and (B1, B4) unto the loading dock and get more B packages (B2, B5, B3, B6).
3. Truck C waits in the loading dock.
4. Workers from the core grab packages A and B and matrix multiply them. Then store results into Truck C. Once Truck C is full, truck C drives to the output.
5. The other trucks arrive with packages B2, B5, B3, B6.
6. Repeat …
Caching in matrix multiplication II

In matrix multiplication $A \times B = C$ we:

Multiply each row of $A$ with \textbf{all columns} from $B$.

As such, memory of $A$ can be reused as often as there are columns in $B$.

Multiply each column of $B$ with \textbf{all rows} of $A$.

As such, memory of $B$ can be reused as often as there are rows in $B$. 
Chinchilla scaling laws and how to estimate compute time

Chinchilla scaling laws (Hoffmann et al., 2022) say we should use 20 training tokens per parameter.

So if our dataset has 380B tokens (The Pile) we need a ~20B model to be efficient. Training transformers incurs 6 FLOPs per parameter per token. So we have:

\[ 380 \times 10^9 \times 20 \times 10^9 \times 6 \text{ FLOPs} = 4.56 \times 10^{22} \text{ FLOPs} \]

A A40 GPU on Hyak has 150 TFLOPS or 150 \times 10^{12} \text{ FLOPS} performance. At 25\% efficiency we have 38\times 10^{12} \text{ FLOPS}.

\[ \frac{4.56 \times 10^{22}}{3.8 \times 10^{13}} \div (60 \times 60 \times 24 \times 365) = 38.05 \text{ GPU years} \]

So to optimally train a model on 380B tokens, we need 38 GPU years.
Calculating the waste of GPT-3 training: I

GPT-3 data set had 300B tokens and model size was 175B:

\[ 300 \times 10^9 \times 175 \times 10^9 \times 6 = 3.15 \times 10^{23} \text{ FLOPs} \]

Chinchilla optimal for 300B tokens is 15B parameters

\[ 300 \times 10^9 \times 15 \times 10^9 \times 6 = 2.27 \times 10^{22} \text{ FLOPs} \]

\[
L(N, D) = E + \frac{A}{N^{0.34}} + \frac{B}{D^{0.28}},
\]

with \( E = 1.69, \ A = 406.4, \ B = 410.7 \). We note that the parameter/data coefficients are both lower.
Calculating the waste of GPT-3 training: II

We use Chinchilla scaling law and increase data and compute equally until we reach the loss for GPT-3.

Solution: 32B parameters on 638B tokens to reach GPT-3 performance.

\[638e9 \times 32e9 \times 6 = 1.25e23 \text{ FLOPs}\]

GPT-3 waste: \(3.15e23 / 1.25e23 = 2.52\)

GPT-3 could have been trained to the same performance with 2.52x less compute.
Putting things together

According to the Chinchilla paper (Hoffmann et al., 2022) one needs 20 tokens per parameter to train in the most cost efficient way.

The internet has about 5T tokens and about 2T of “high quality” tokens.

Max effective model size is 250 - 100B parameters.

For 250B - 100B parameters, Mixture of Experts are about 3-5x more efficient.

Chinchilla scaling is 2.5x more efficient compared to GPT-3 training.

-> Chinchilla mixture of expert training is 8x to 13x more efficient than GPT-3 training
Language modeling

Objective: Take a sequence of words and predict the next word.

Why is this a good objective:

- Learn grammar and style first
- Then model the world. You need to model people in order to understand that they could say/write next -> emotional state, political affiliation, social status, social situation, current time (past/future/present), fictional or non-fictional
Transformers

Example: “Her dog felt guilty. Daisy looked down avoiding eye contact. She was fully aware of the ___”

How to think about transformers. A simplification:

1. Create word embeddings. Each word has many “features”. Each feature is an association of what is going on for this word: grammar, time, emotional state, social situation, environment, animate vs inanimate.
2. Combine association for a word to create new condensed association for that word
3. Weighted sum across tokens for each associations to create new context-enriched associations
Mixture of Experts
Transformers vs mixture of experts

Some associations are mutually independent. Associations of heart medicine not very useful to answer questions about astrophysics. Computing heart medicine associations on astrophysics data is a waste of compute.

Can we arrange associations into distinct packages that activate when needed rather than being activated during any context?
The Transformer is wasting compute

Transformer
Feedforward layer

Inputs
- Medicin
- Law
- Math
- Code

Outputs
Expert perspective

Inputs

Router

Expert Feedforward layer

- Medicin
- Law
- Math
- Code

Outputs
Outrageously Large Neural Networks: The Sparsely-Gated Mixture-of-Experts Layer

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GShard: Scaling Giant Models with Conditional Computation and Automatic Sharding

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GShard

Three parts:

1. Expert architecture
2. Extra loss function to avoid degeneration
3. Load-balancing to avoid waiting for slowest expert
GShard: Architecture

For each token:

1. Select expert via top-k softmax
   \[ G(x) = \text{Softmax}(\text{KeepTopK}(H(x), k)) \]

2. Pass through expert, then multiply by softmax value

\[ y = \sum_{i=1}^{n} G(x)_i E_i(x) \]

\[ G_{s,E} = \text{GATE}(x_s) \]

\[ \text{FFN}_e(x_s) = w_0_e \cdot \text{ReLU}(w_i_e \cdot x_s) \]

\[ y_s = \sum_{e=1}^{E} G_{s,e} \cdot \text{FFN}_e(x_s) \]
GShard: Auxiliary loss function

Problem: at the start of training the expert that is best might be selected again and again which leads to degeneration. As such, we penalize the distribution of experts.

\[ L = \text{loss} + \text{auxiliary loss} \]

\[ L_{\text{aux}} = \text{num\_experts} \times \text{fraction of tokens per expert} \times \text{mean(gate probability)} \]

- Expert has mean probability close to 0 -> 0 loss
- Expert has mean probability close to \(1/2E\) -> \(E^{1/2E \times 1/2E} = 1/4E\) loss
- Expert has mean probability close to \(1/E\) -> \(E^{1/E \times 1/E} = 1/E\) loss
- Expert has mean probability close to \(2/E\) -> \(E^{2/E \times 2/E} = 4/E\) loss
- Expert has mean probability close to 1 -> \(E^{E \times 1} = E^2\) loss
Gshard: Load balancing

Problem: If we compute multiple experts in parallel with a different amount of tokens, some experts may have more tokens than others and take longer -> All experts need to wait for the slowest expert.

Solution: We have a capacity limit of \( \sim \frac{\text{total\_tokens}}{\text{num\_experts}} \). Any tokens going beyond this limit will be set to zero and will not be routed to any expert.
Results
Issues: Complicated and slow communication

- Extra loss
- Load-balancing via overflow

Can we do better?
BASE Layers: Simplifying Training of Large, Sparse Models

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UNIFIED SCALING LAWS FOR ROUTED LANGUAGE MODELS

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DeepMind Google Research†
BASE layers approach

1. Randomly assign tokens, then rerank locally
2. Learn a centroid for each expert, compute similarity score between tokens and centroids
3. Use similarity score to rerank tokens to experts (linear assignment problem)

Figure 1. Overview of a BASE layer. Each worker contains a separate expert module. During training, we compute a balanced assignment of tokens such that each worker sends an equal number of tokens to each expert. By softly mixing in the expert module, experts can learn to specialize for particular types of tokens.
BASE layers: architecture

Regular transformer layers + BASE layers instead of feedforward network for every other layer.

h = input token, f_a = expert, w_a = expert_centroid, sigma = logistic sigmoid

t = index into sequence (token)

\[ \sigma(h_t \cdot w_{a_t}) f_{a_t}(h_t) + h_t, \]

Training: Assign tokens equally to each expert

Evaluation: Assign tokens to highest scoring expert
Table 2. Number of tokens processed per second during training by different models. BASE computes updates faster than other approaches that divide models over multiple workers, due to reduced communication overheads. This allows a 43B parameter model to be trained at 90% of the speed of a 1.5B data parallel baseline.
Remaining issue: Slow communication
Branch-Train-Merge: Embarrassingly Parallel Training of Expert Language Models

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(a) Fully Synchronized Training
Train one LM on mono-corpus, synchronizing weights across all GPUs

(b) Embarrassingly Parallel Training
Train k independent LMs in parallel on one data domain each, without synchronizing across LMs
Branch-Train-Merge: Architecture

It’s just a transformer! So no changes to the architecture or no new loss.
Branch-Train-Merge: Training

How to train:

- **Branch**: Take a reference LLM or train a new one for a couple thousand steps
- **Branch**: Copy its weights for each domain
- **Train**: Feed data of each domain through its designated “expert”
- **Train**: Train all experts independently (no communication needed)
- **Merge**: Merge experts into a single model. This is done through evaluation on a validation set.
Branch-Train-Merge: Results. Better than transformers
Branch-Train-Merge: Results. Faster than transformers.

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<thead>
<tr>
<th></th>
<th>Average updates per second, normalized (†)</th>
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<tbody>
<tr>
<td></td>
<td>fully synchronized</td>
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<tr>
<td>125M</td>
<td>1.00</td>
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<td>350M</td>
<td>1.00</td>
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<tr>
<td>750M</td>
<td>1.00</td>
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<tr>
<td>1.3B</td>
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Conclusion

If we want to maximize \( \min(\text{compute/waste, data movement/waste}) \) then:

1. GPUs balance compute and data movement
2. Scaling laws help us reduce waste in our training setup
3. Mixture of experts help us to reduce waste by reducing unneeded computation
   a. BASE layers balances compute and data movement compared to GShard
   b. Branch-train-merge eliminates data movement across experts entirely
Thank you!
Questions / Comments?
Why does this tenet make sense: Evidence from neuroscience

Study brains of all mammals.

Finding (1): brain structure correlated with evolutionary tree structure
Why does this tenet make sense: Humans have the most compute

Finding (2): Intelligence ~ number of neurons

Finding (3): Primate neurons scale differently

- A cat has 50x more neurons than a bee
- A dog has 2x more neurons than a cat
- A dolphin/elephant/chimpanzee/crow has 5x more neurons than a dog
- A humans has 10x more neurons than a chimpanzees
Why does this tenet make sense: Humans produce the most energy

Finding (4): Intelligence is energy limited: Chose 1: (a) large body, (b) large brain
Finding (5): Humans are more energy efficient and can afford more intelligence.