Switch Transformers: Scaling to Trillion Parameter Models with Simple and Efficient Sparsity

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Highlights

Paper presents a collection of techniques/tips that seem to work well for LM

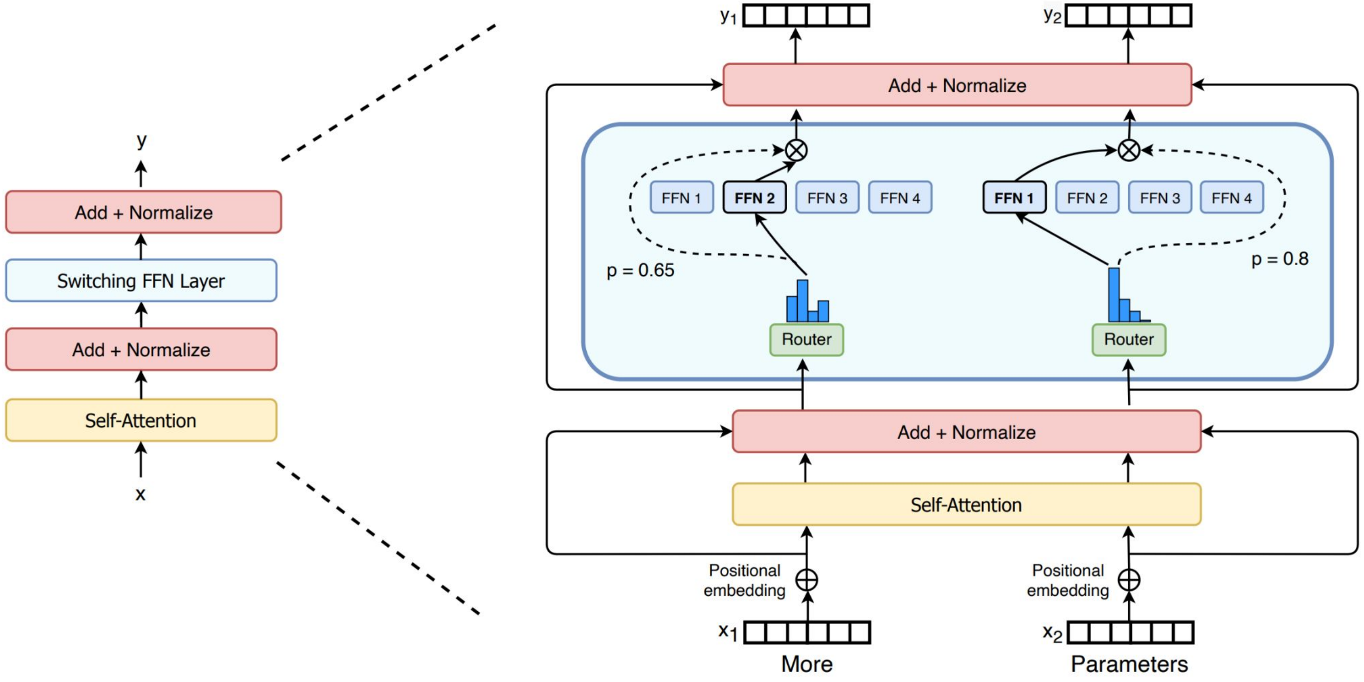
- Simplifies MoE architecture (each token routed to 1 expert)
- Scaling results -> scaling model params while keeping FLOPs per token constant leads to better results
- Sparse MoE works great:
    - Switch is faster to train for similar performance to dense model (T5)
    - Finetuning performance is better
    - Distillation is also effective in retaining teacher's performance while compressing model size

Why is this paper important?

- From scaling laws, we know that larger models are more sample-efficient
    - Switch transformers helps scale while keeping inference cost the same
- Dense models are harder to train, MoE is complicated
    - Shows that a single expert is sufficient, thus reducing complexity of MoE
    - Provide tips and tricks for stable training and distillation
- Adds a new dimension for scaling laws: increasing model size while keeping FLOPs constant also improves performance (i.e., sparsity)
    - Different from just increasing param. count (which is equivalent to more compute)

How is sparsity achieved?

- Sparsity due to activation of only one expert



Routing

Normal MoE

$$p_i(x) = \frac{e^{h(x)_i}}{\sum_j^N e^{h(x)_j}}.$$

Gate value for i^{th} expert

$$y = \sum_{i \in \mathcal{T}} p_i(x) E_i(x).$$

Layer output
(lin. combination of experts in T)

For switch transformers, we just take argmax(p_i)

Why just one expert?

- Reduced routing computation
- Batch size of each expert can be at least halved
  - For top-2, each token is processed twice, for top-3, each token is processed thrice…
- Routing implementation is simplified & communication cost reduced
- Since forward pass FLOPs is now constant, you can scale without worrying about increased inference computation
  - Can leverage scaling -> better performance

Distributed Switch Implementation

- Tensor shapes are statically determined at compile time
- Use expert capacity -> number of tokens each expert computes

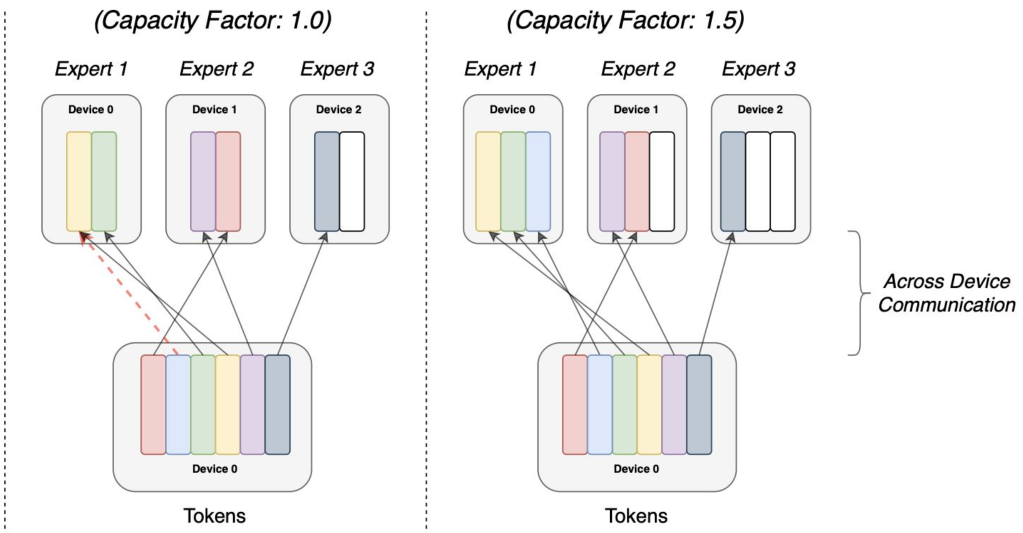
$$\text{expert capacity} = \left(\frac{\text{tokens per batch}}{\text{number of experts}}\right) \times \text{capacity factor}.$$

- Low capacity factor -> dropped tokens
- High capacity factor -> increased computation/communication cost
- Dropped tokens passed to next layer through residual connections

Distributed Switch Implementation

Terminology

- **Experts:** Split across devices, each having their own unique parameters. Perform standard feed-forward computation.
- **Expert Capacity:** Batch size of each expert. Calculated as
- (tokens_per_batch / num_experts) * capacity_factor
- **Capacity Factor:** Used when calculating expert capacity. Expert capacity allows more buffer to help mitigate token overflow during routing.



Load Balancing Loss

- Auxiliary loss added to encourage balanced token routing for N experts

$$\text{loss} = \alpha \cdot N \cdot \sum_{i=1}^{N} f_i \cdot P_i$$

$$f_i = \frac{1}{T} \sum_{x \in \mathcal{B}} \mathbb{1}\{\text{argmax}\, p(x) = i\}$$

fraction of tokens to expert i

$$P_i = \frac{1}{T} \sum_{x \in \mathcal{B}} p_i(x).$$

router probability to expert i

- Authors claim this loss encourages uniform routing since it is minimized under uniform distribution (not necessarily true!)

Load Balancing Loss

- Authors claim loss is minimized value for both f_i and P_i is 1/N. But this is not true. Consider N=2, T=3

	Expert 1	Expert 2
Token 1	0.51	0.49
Token 2	0.51	0.49
Token 3	0	1

$$\sum_{i=1}^{N}(f_i \cdot P_i) = \sum_{i=1}^{N}(\frac{1}{N} \cdot \frac{1}{N}) = \frac{1}{N}$$

$$\sum_{i=1}^{N} f_i \cdot P_i = (1/2).(1/2) + (1/2).(1/2)$$

Table of softmax values (p_i)

$$f = \left(\frac{2}{3}, \frac{1}{3}\right), \qquad P = (0.34, 0.66), \qquad \langle f, P \rangle = 0.447 < \frac{1}{2}$$

Credit: https://www.cs.princeton.edu/courses/archive/fall22/cos597G/lectures/lec16.pdf

Baselines

- T5
  - Released in 2020
  - Family of models: 60M, 220M (T5-Base), 740M (T5-Large), 3B, 11B
  - Represents dense models
- MoE Transformers
  - Released in 2017
  - In this paper, top-2 routing is used for comparison
  - FLOPs is larger than Switch Transformers because each expert applies its own FFN

Results

- Masked language modelling task where 15% of tokens are masked
- C4 dataset

Model	Capacity Factor	Quality after 100k steps (↑) (Neg. Log Perp.)	Time to Quality Threshold (↓) (hours)	Speed (↑) (examples/sec)
T5-Base	—	-1.731	Not achieved†	1600
T5-Large	—	-1.550	131.1	470
MoE-Base	2.0	-1.547	68.7	840
Switch-Base	2.0	-1.554	72.8	860
MoE-Base	1.25	-1.559	80.7	790
Switch-Base	1.25	-1.553	65.0	910
MoE-Base	1.0	-1.572	80.1	860
Switch-Base	1.0	-1.561	**62.8**	1000
Switch-Base+	1.0	**-1.534**	67.6	780

- Switch Transformers outperforms MoE and T5 on speed-quality basis
- Switch has smaller computational footprint
- Switch performs better at lower capacity factors

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MoE beats Switch here

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Increase computation elsewhere (non-expert part) to match MoE compute speed, and performance is better

Results

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Speed-quality pareto optimality is somewhere here (reduce capacity factor), increase compute in non-expert layers

Techniques for improving training

- Selective precision (float32 is slower to compute, also means you transferring more data between layers on potentially different devices)
- Reduced initialization scale
- Higher regularization of experts

Selective Precision

- Using only bfloat16 leads to instability (esp. during exponentiation)
- Using only float32 will increase costs
- Selectively cast router input to float32 precision - float32 only used within body of router function

```
# Convert input to softmax operation from bfloat16 to float32 for stability.
router_logits = mtf.to_float32(router_logits)

# Probabilities for each token of what expert it should be sent to.
router_probs = mtf.softmax(router_logits, axis=-1)

        .
        .
        .

# Cast back outputs to bfloat16 for the rest of the layer.
combine_tensor = mtf.to_bfloat16(combine_tensor)
```

Model (precision)	Quality (Neg. Log Perp.) (↑)	Speed (Examples/sec) (↑)
Switch-Base (float32)	-1.718	1160
Switch-Base (bfloat16)	-3.780 [*diverged*]	**1390**
Switch-Base (Selective precision)	**-1.716**	1390

Smaller Parameter Initialization

- Weight matrices initialized by sampling from a truncated normal distribution with mean $\mu = 0$ and standard deviation $\sigma = \sqrt{s/n}$

- Reduce default initialization scale s = 1.0 to 0.1

Model (Initialization scale)	Average Quality (Neg. Log Perp.)	Std. Dev. of Quality (Neg. Log Perp.)
Switch-Base (0.1x-init)	**-2.72**	**0.01**
Switch-Base (1.0x-init)	-3.60	0.68

Table 3: Reduced initialization scale improves stability. Reducing the initialization scale results in better model quality and more stable training of Switch Transformer. Here we record the average and standard deviation of model quality, measured by the negative log perplexity, of a 32 expert model after 3.5k steps (3 random seeds each).

Higher Regularization of Experts

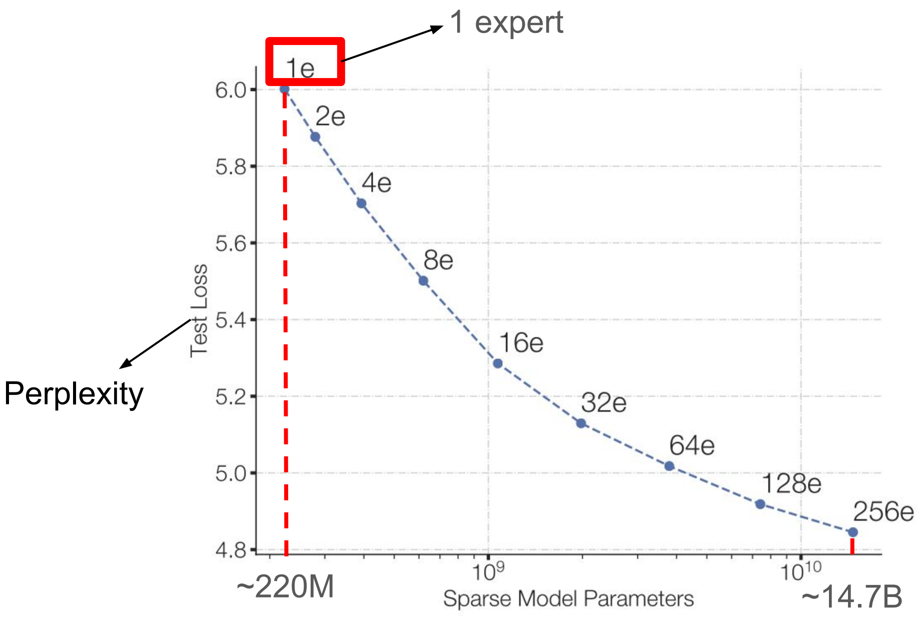
- Many finetuning tasks have very few examples -> leads to overfitting
- Switch Transformers have more parameters -> severe overfitting
- Increase dropout inside experts
    - Increasing dropout across all layers leads to worse performance

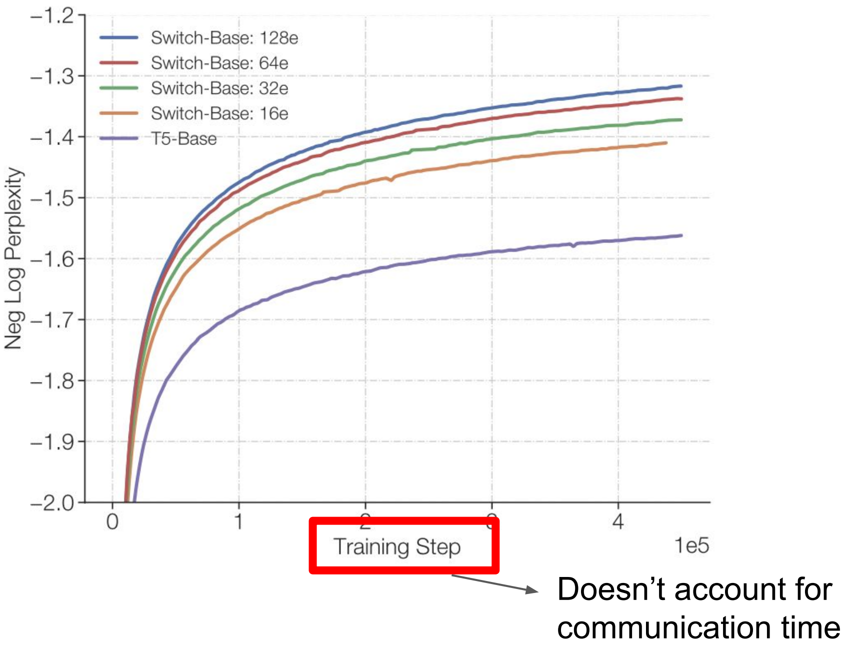
Model (dropout)	GLUE	CNNDM	SQuAD	SuperGLUE
T5-Base (d=0.1)	82.9	**19.6**	83.5	72.4
Switch-Base (d=0.1)	84.7	19.1	**83.7**	**73.0**
Switch-Base (d=0.2)	84.4	19.2	**83.9**	**73.2**
Switch-Base (d=0.3)	83.9	19.6	83.4	70.7
Switch-Base (d=0.1, ed=0.4)	**85.2**	**19.6**	**83.7**	**73.0**

Table 4: Fine-tuning regularization results. A sweep of dropout rates while fine-tuning Switch Transformer models pre-trained on 34B tokens of the C4 data set (higher numbers are better). We observe that using a lower standard dropout rate at all non-expert layer, with a much larger dropout rate on the expert feed-forward layers, to perform the best.

Scaling on a step-basis

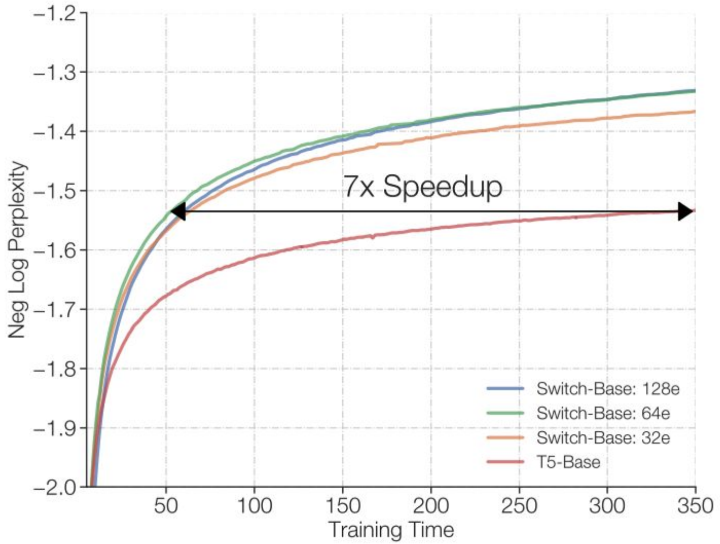
- Scaling experts (more params.) when training for fixed number of steps





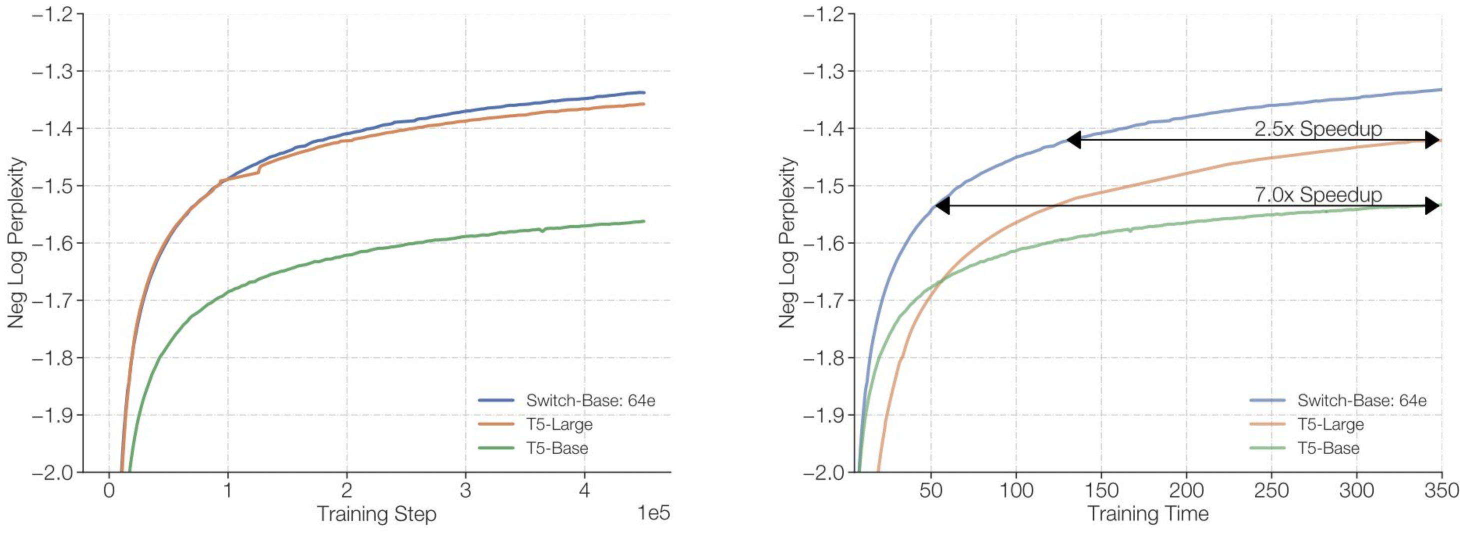
Scaling properties on time basis

- Switch has more communication costs than T5
- For fixed training duration and comp. budget, Switch is better



Scaling vs larger dense model

- Increase sparsity (num. experts) or model density?



Downstream Experiments

- Finetuning
- Distillation
- Multilingual learning

Downstream: Finetuning results

- Switch is better

Model	GLUE	SQuAD	SuperGLUE	Winogrande (XL)
T5-Base	84.3	85.5	75.1	66.6
Switch-Base	**86.7**	**87.2**	**79.5**	**73.3**
T5-Large	87.8	88.1	82.7	79.1
Switch-Large	**88.5**	**88.6**	**84.7**	**83.0**

Model	XSum	ANLI (R3)	ARC Easy	ARC Chal.
T5-Base	18.7	51.8	56.7	**35.5**
Switch-Base	**20.3**	**54.0**	**61.3**	32.8
T5-Large	20.9	56.6	**68.8**	**35.5**
Switch-Large	**22.3**	**58.6**	66.0	**35.5**

Model	CB Web QA	CB Natural QA	CB Trivia QA
T5-Base	26.6	25.8	24.5
Switch-Base	**27.4**	**26.8**	**30.7**
T5-Large	27.7	27.6	29.5
Switch-Large	**31.3**	**29.5**	**36.9**

Distillation Results

Perplexity

Technique	Parameters		Quality (↑)
T5-Base	223M		-1.636
Switch-Base	3,800M		-1.444
Distillation	223M	(3%)	-1.631
+ Init. non-expert weights from teacher	223M	(20%)	-1.598
+ 0.75 mix of hard and soft loss	223M	(29%)	-1.580
Initialization Baseline (no distillation)			
Init. non-expert weights from teacher	223M		-1.639

Non-expert layers have same dimensions

Ground truth loss

Matching output logits of teacher model (Switch)

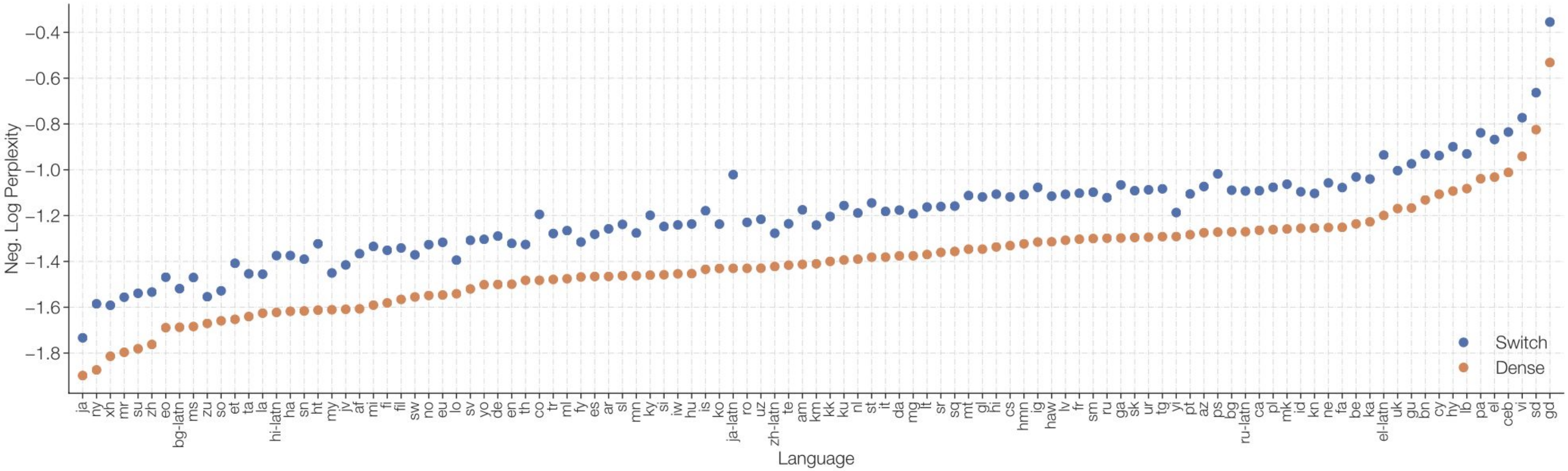
Loss = a.L(hard) + (1-a).L(soft)

Distillation Results

	Dense	Sparse				
Parameters	223M	1.1B	2.0B	3.8B	7.4B	14.7B
Pre-trained Neg. Log Perp. (↑)	-1.636	-1.505	-1.474	-1.444	-1.432	-1.427
Distilled Neg. Log Perp. (↑)	—	-1.587	-1.585	-1.579	-1.582	-1.578
Percent of Teacher Performance	—	37%	32%	30 %	27 %	28 %
Compression Percent	—	82 %	90 %	95 %	97 %	99 %

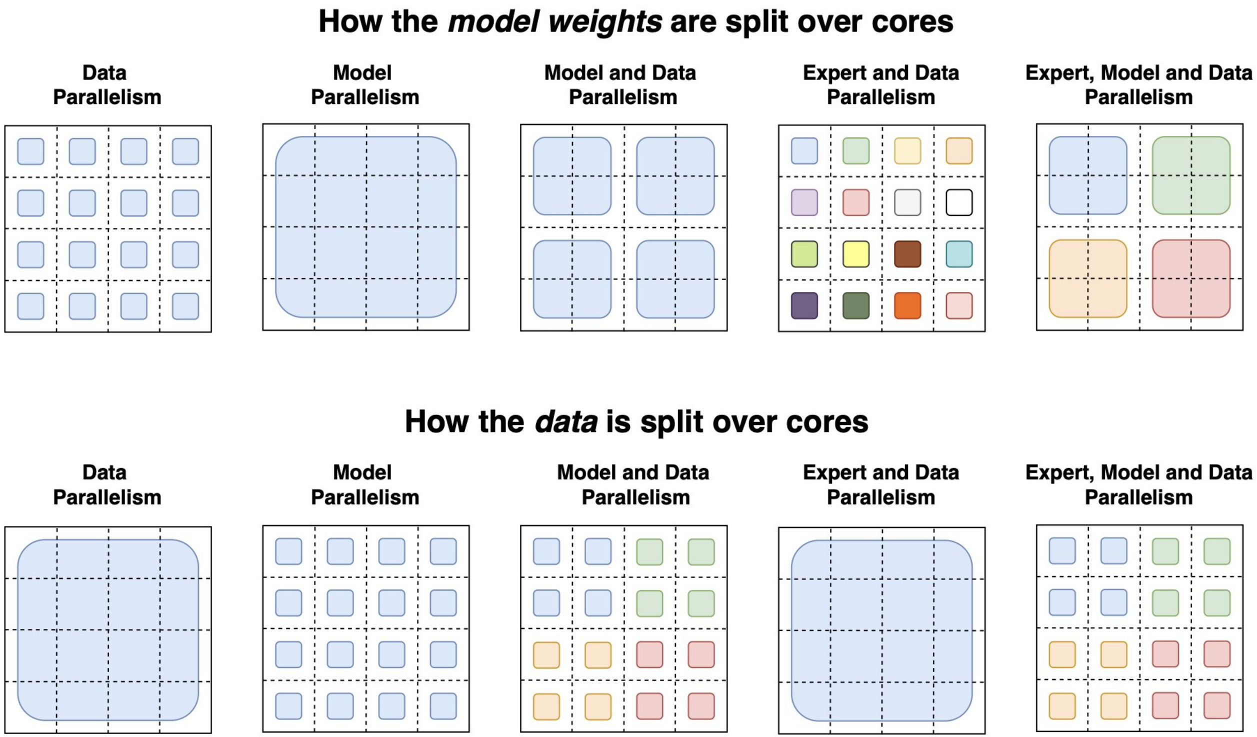
Multilingual learning

- Train on multilingual variant of C4 with 101 languages
- mSwitch is better than mT5 on all languages



Scaling strategies - Data, Model, Expert parallelism

Only scaling experts will give diminishing returns



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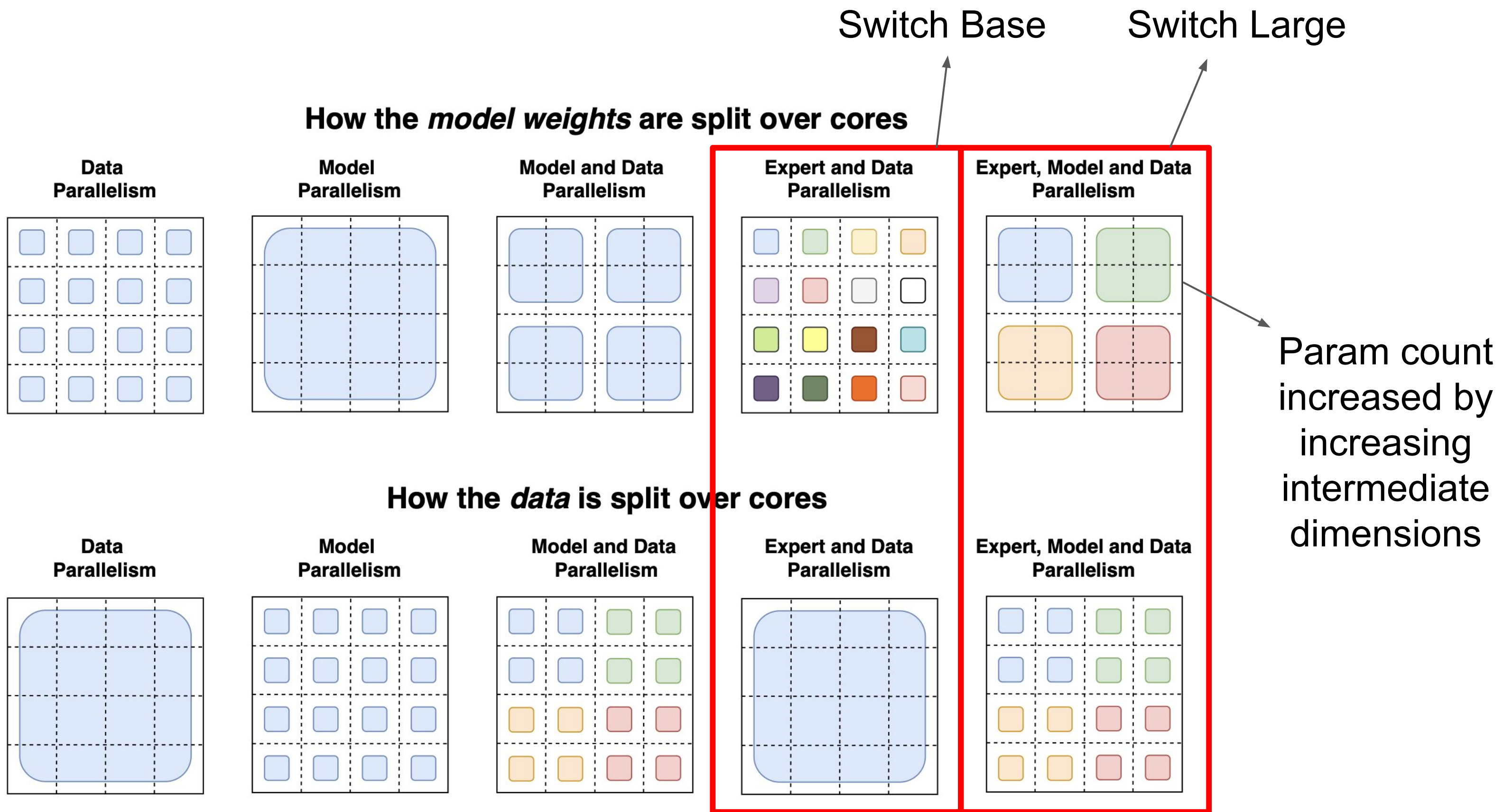

Scaling to trillion parameters

Model	Parameters	FLOPs/seq	d_{model}	FFN_{GEGLU}	d_{ff}	d_{kv}	Num. Heads
T5-Base	0.2B	124B	768	✓	2048	64	12
T5-Large	0.7B	425B	1024	✓	2816	64	16
T5-XXL	11B	6.3T	4096	✓	10240	64	64
Switch-Base	7B	124B	768	✓	2048	64	12
Switch-Large	26B	425B	1024	✓	2816	64	16
Switch-XXL	395B	6.3T	4096	✓	10240	64	64
Switch-C	1571B	890B	2080		6144	64	32

Model	Expert Freq.	Num. Layers	Num Experts	Neg. Log Perp. @250k	Neg. Log Perp. @ 500k
T5-Base	–	12	–	-1.599	-1.556
T5-Large	–	24	–	-1.402	-1.350
T5-XXL	–	24	–	-1.147	-1.095
Switch-Base	1/2	12	128	-1.370	-1.306
Switch-Large	1/2	24	128	-1.248	-1.177
Switch-XXL	1/2	24	64	**-1.086**	**-1.008**
Switch-C	1	15	2048	-1.096	-1.043

Scaling to trillion parameters

~10x less FLOPs

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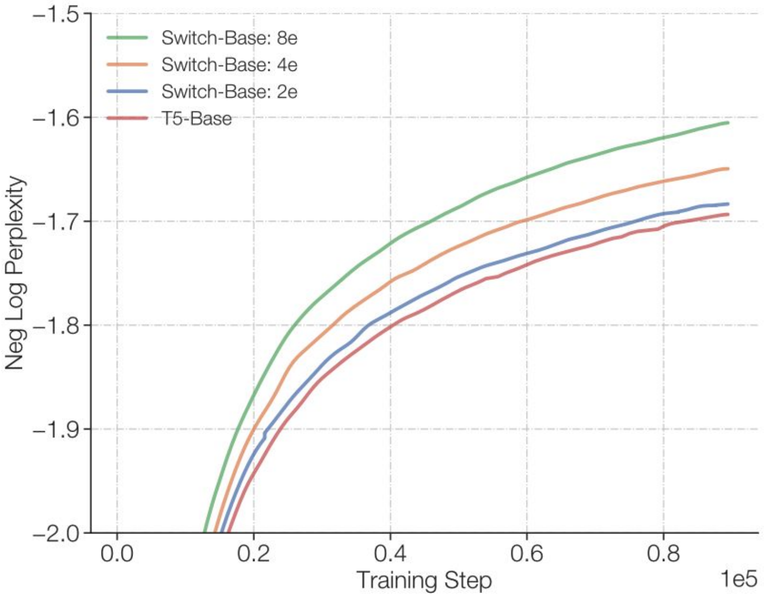
Size achieved by increasing experts, but worse performance than XXL

Additional Discussion

- Switch transformers works for smaller models too
- Even with 2 cores (1 expert per core), Switch is a better choice



Summary

- Bigger models are just better
- Don't need multiple experts, a single expert is sufficient
- Use the following techniques for better training:
    - Mixed precision training (higher precision when doing exponentiation, etc.)
    - Smarter initialization with smaller values
    - Regularize using dropout

Additional Discussion

- Load balancing loss assumption is wrong (uniform routing does not minimize the loss), but still seems to work
  - This could mean that many tokens must pass through residual connection under optimal training
- How to reconcile uniform load distribution with expert specialization?
  - Specialization (polysemanticity) is observed in neurons
  - Do experts specialize in certain tasks (nouns, areas like english, grammar, etc.)?
  - If so, wouldn’t router probability depend on input distribution? Inputs dealing with math might get routed to expert 1 more frequently, english reasoning to expert 2, etc.
- Simply scaling experts leads to diminishing returns (Switch-C)
  - Increasing sparsity by just increasing expert count leads to diminishing returns even at 1T
  - Human brain has over 100T synapses (parameters)!
  - Would the training suggestions provided by authors scale to even larger sizes?

Thank You!