MatFormer: Nested Transformer for Elastic Inference

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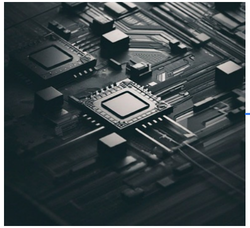
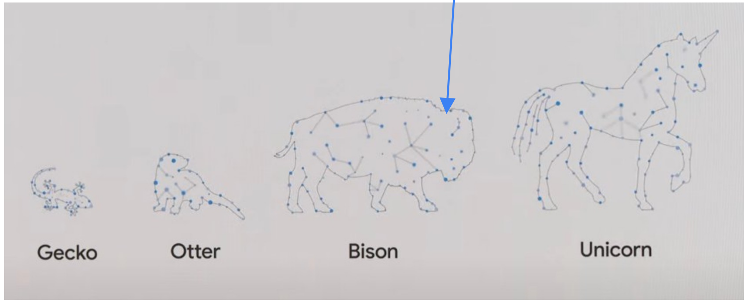
Large Models: Deployment Story



Deployment Constraints
(RAM, Latency, QPS…)

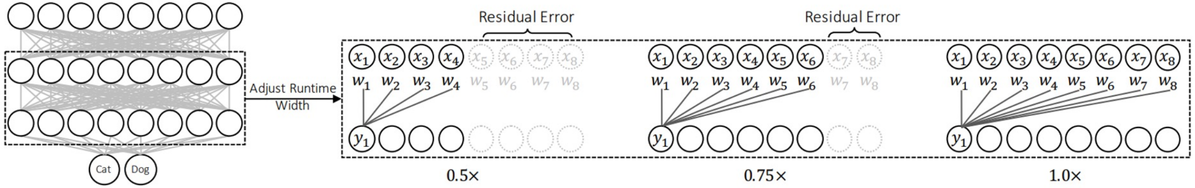
- Typically only a few models to choose from
  - Might have to select say Llama 13B even if capacity for Llama 40B
- Distillation/pruning requires additional training



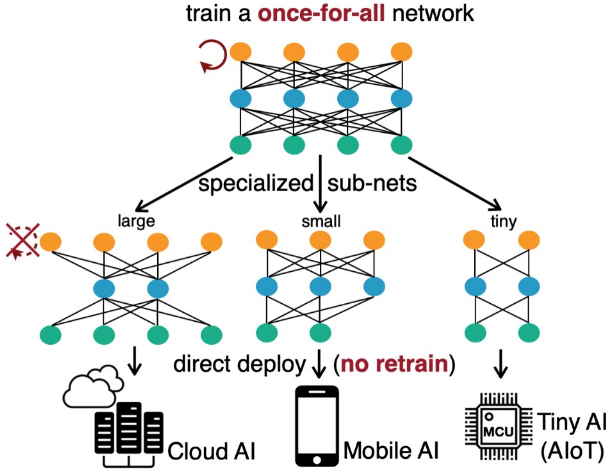
PALM 2

Goal: *design a "universal" model from which hundreds of accurate models can be extracted*

Existing Solutions towards MatFormer



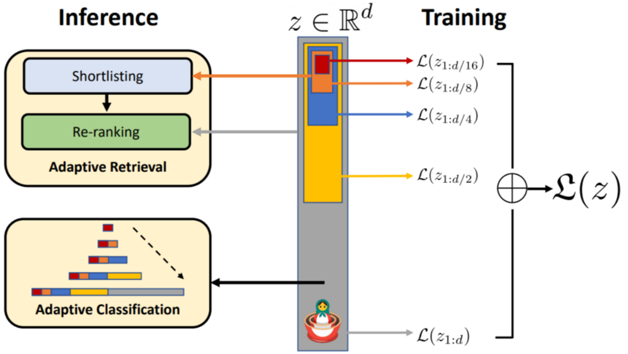
(Universal) Slimmable Networks (Yu & Huang ICLR 2019; ICCV 2019)



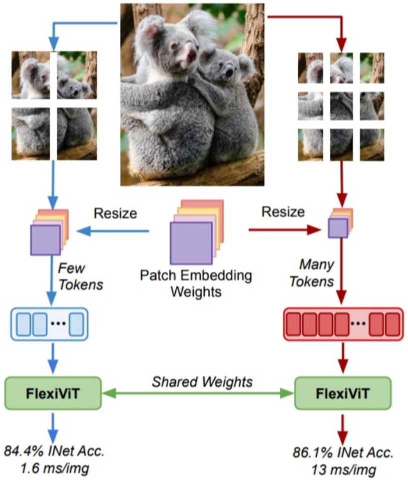
Once-for-All (Cai et al., ICLR 2020)

- Primarily focused on CNNs
- Training routines w/
    - Modifications to batchnorm
    - Sampled submodels
    - Distillation from largest model
- Longer/costlier training routines

Existing Solutions towards MatFormer



Matryoshka Representation Learning (Kusupati et al., NeurIPS 2022)



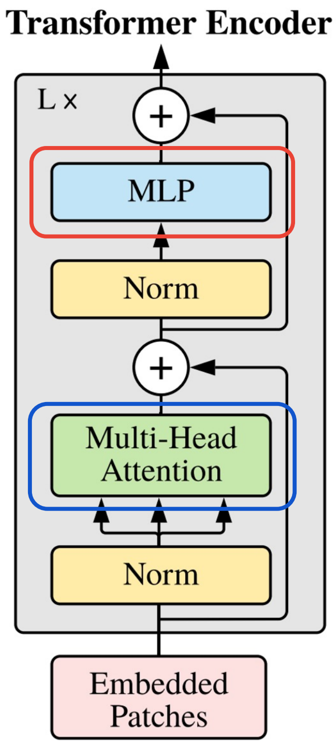
FlexiViT (Beyer et al., CVPR 2023)

Flexibility in output and input space respectively

MatFormer: Nested Substructure

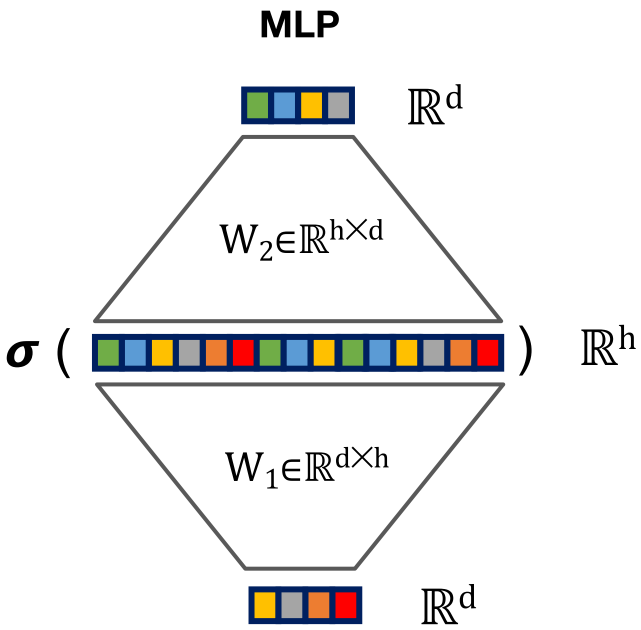
- Works for Transformers – without modifications to fundamental blocks
- Joint training: No subsampling or distillation
- Significantly cheaper training cost that equivalent methods while being more accurate
- 4 granularities sufficient to span a wide range of constraints.

Transformer



MLP: **~80%** of the cost

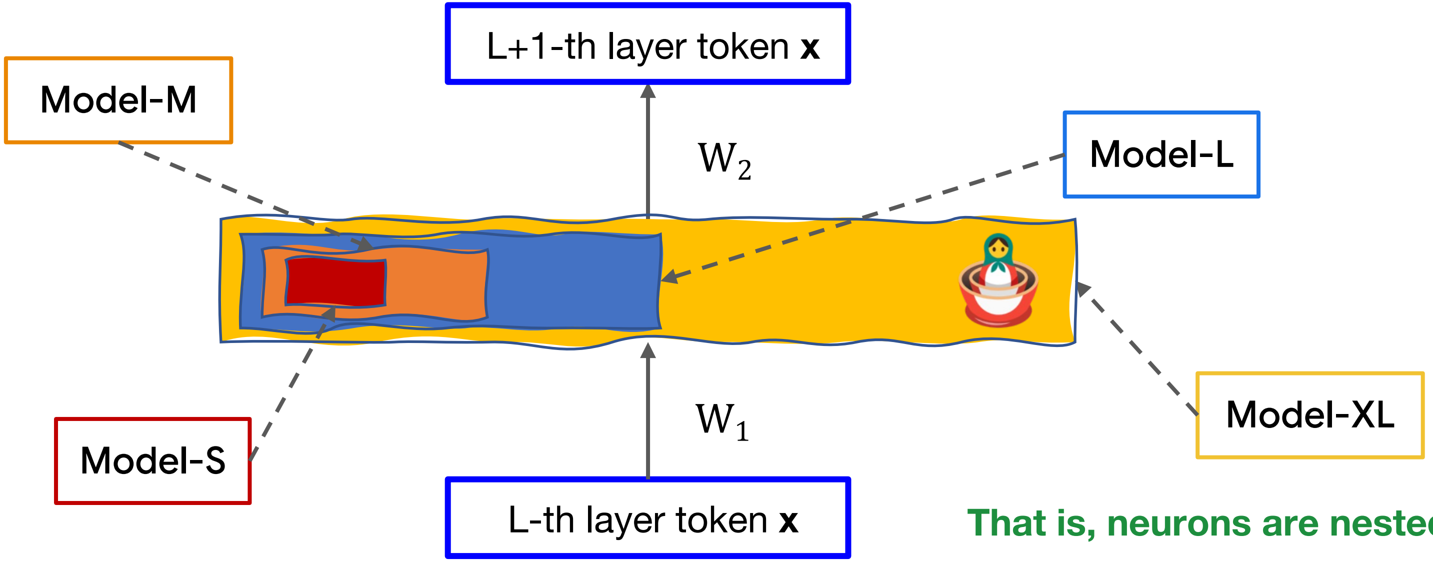
Attention: **~20%** of the cost



h = **4*d** to **12*d** typically

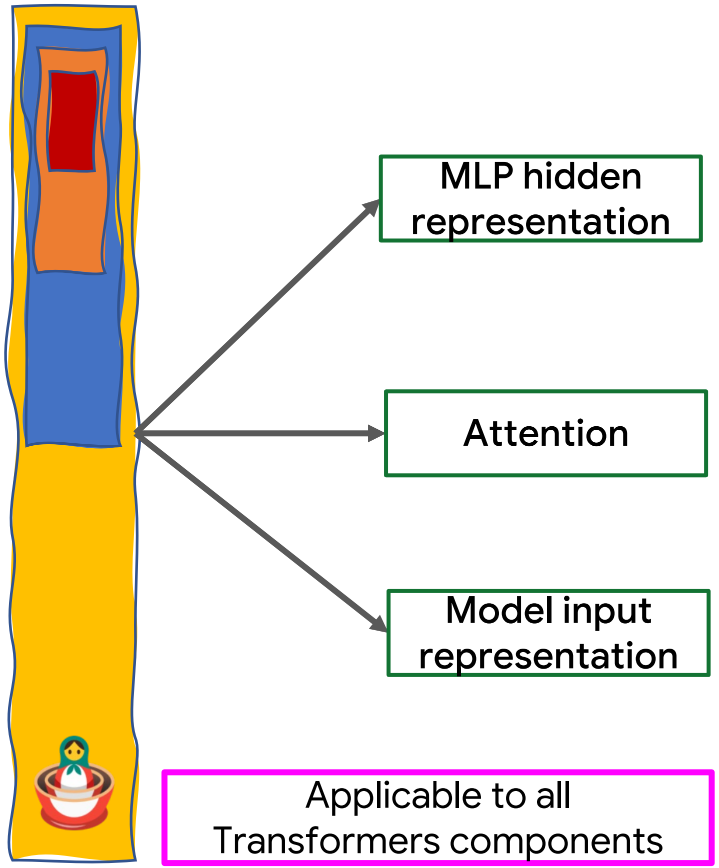
MatFormer: Matryoshka Transformer

- **MatFormer** builds upon [MRL]
- Apply MRL to MLP layer in each transformer block



That is, neurons are nested in each other.

MatFormer: Generality & Training

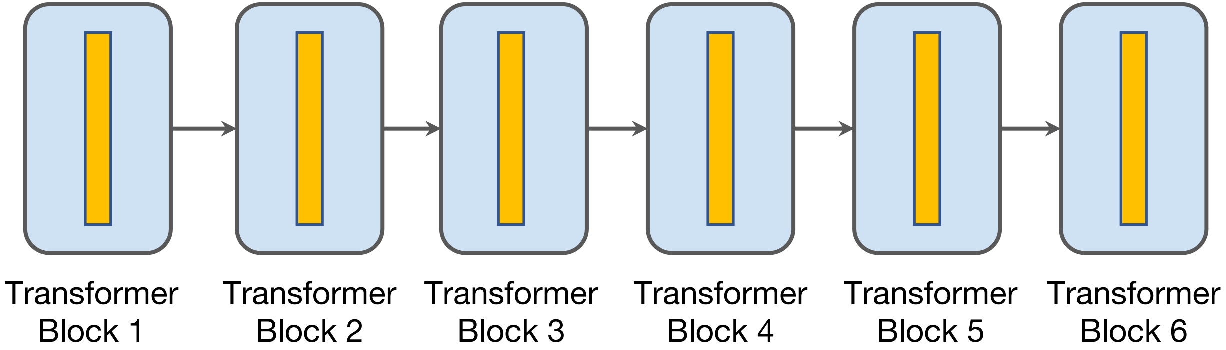


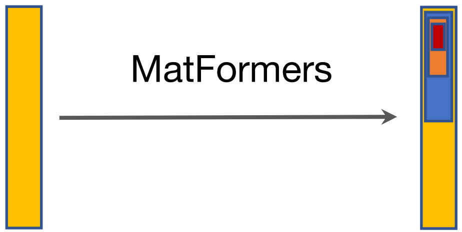
Recipe:

- Pick XL model architecture
- Pick **G** granularities for nesting eg., **G = 4**
- Jointly optimize **G** shared models akin to MRL
- Matformer train cost **<** **total cost of training each granularity from scratch**
- MatFormer can also be induced w/ Fine-tuning

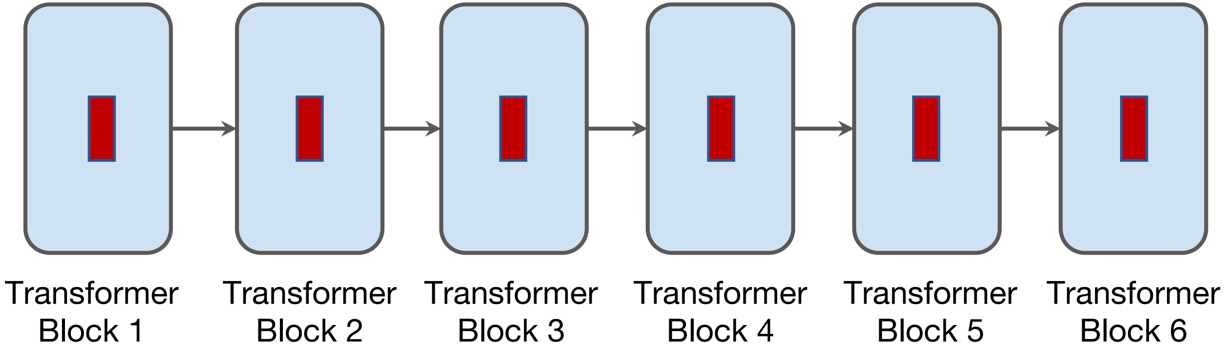
Can generate **1000s** of models not just **4**

Mix'n'Match & Routing on MatFormer





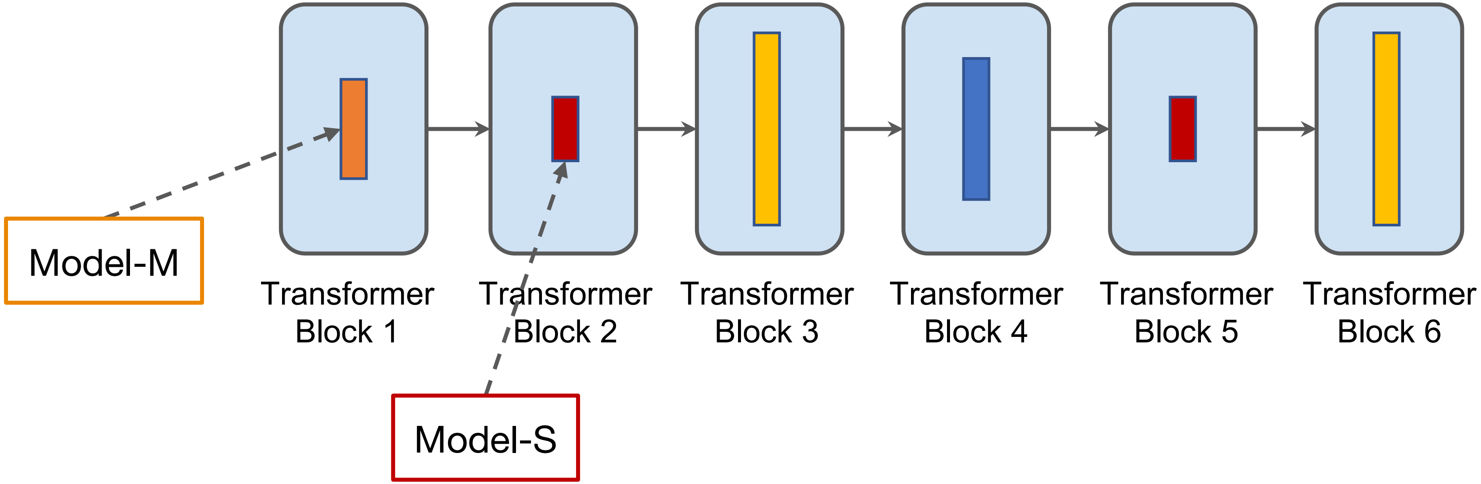
Mix'n'Match & Routing on MatFormer



This gives only say 4 models.

So where do we get 1000s of models???

Mix'n'Match & Routing on MatFormer



- **Mix’n’Match:** 100s (combinatorial) of *static (on-demand)* models for all accuracy-compute
- **Routing:** Token based routing akin to MoE to realize *dynamic* computation

MatLM: MatFormers for Language Modeling

- Standard setting from Lamda (Thoppilan et al.)
- **G = 4** granularities – change the MLP hidden dims!
  - **XL** – hidden_dim (hd), **L** – hd/2, **M** – hd/4, **S** – hd/8.
- Nomenclature: MatFormer-XL, MatFormer-L, MatFormer-M, MatFormer-S
  - Independently Trained Models: Baseline-XL, Baseline-L, Baseline-M, Baseline-S
- *7 different "XL" model scales:* from 78M up to 2.6B parameters.
  - 78M, 180M, 310M, 463M, 850M, 1.3B, 2.6B

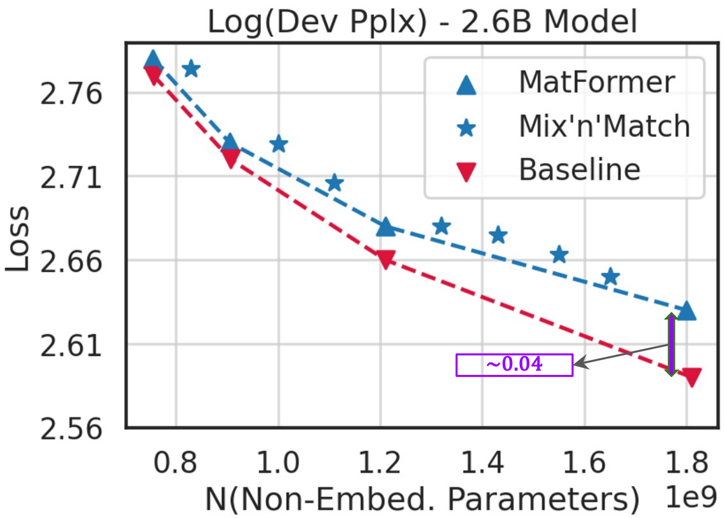
MatLM: Key Findings

- Little to **no loss in test pplx** and **GPT3 1-shot downstream evals**.
  - For each granularity, i.e., accuracy(MatFormer-Z) ~ accuracy(Baseline-Z)
  - Z ∈ [XL, L, M, S]

- Able to read models for *free* using Mix'n'Match
  - Mix'n'Match interpolates well between the 4 granularities

- Side effects: consistency with large model, gains over Speculative Decoding

Language Modeling with 2.6B model: Mix’n’Match



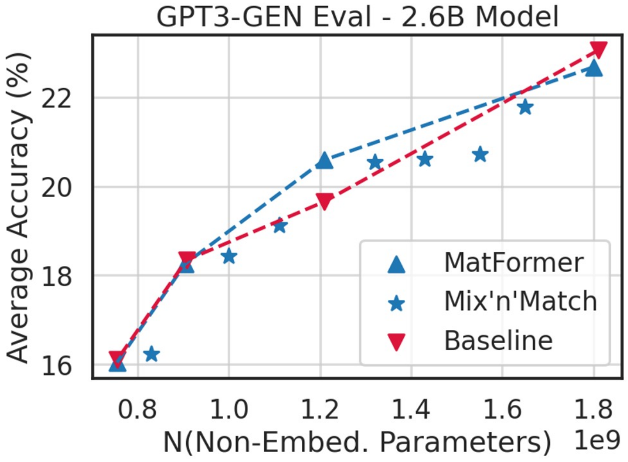
Trained for: 160B tokens

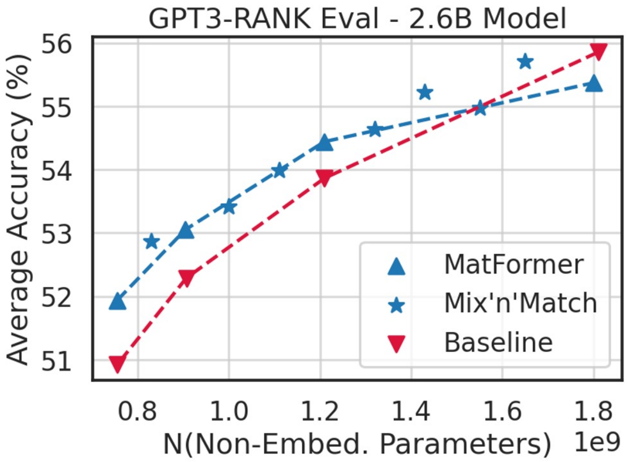
Decoder-only model w/ same hparameters for baseline & MatFormer

- XL model size: 2.6B
  - We read-off L, M, S models for matformer
  - Baselines trained from scratch for all granularities
- Log pplx within 0.04 of the baseline for 2.6B model!
  - Downstream evals almost match (see next slide)
- All the ★ are for “free” – *they were never trained for*
  - We just read them from Matformer-XL

Language Modeling with 2.6B model: Mix’n’Match

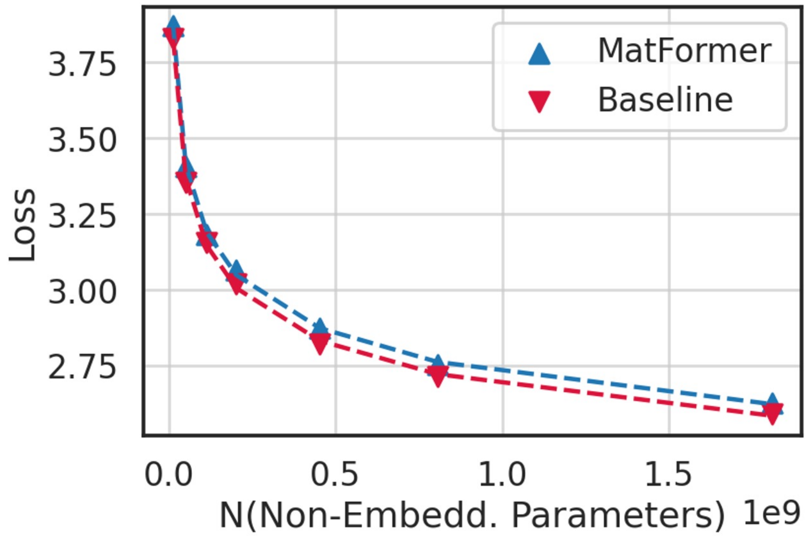
1-shot GPT-evals

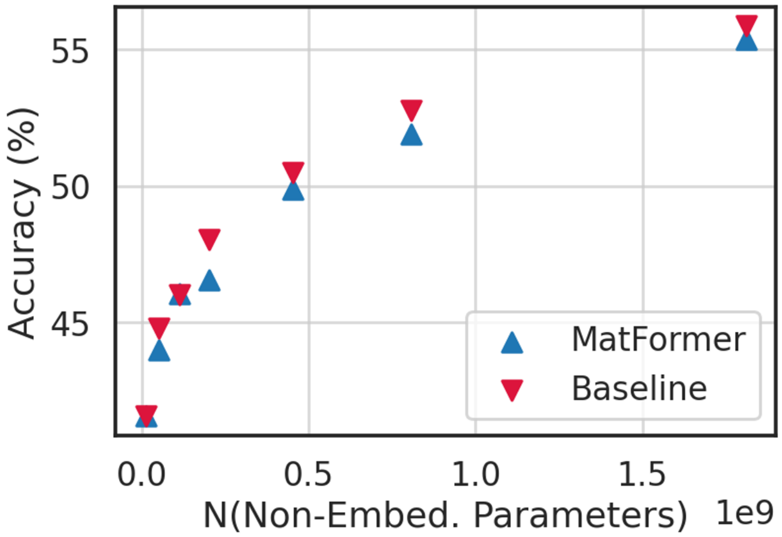




- Almost matching accuracy for MatFormer–[XL, L, M, S] models against Baselines
- We get all the intermediate models denotes by ★ for “free”
  - No extra training!
  - For GPT-3 Rank: ★ models almost lie on a line interpolating trained MatFormer models (XL, L, M, S)

Language Modeling: Scaling Plots for Universal Model (XL)





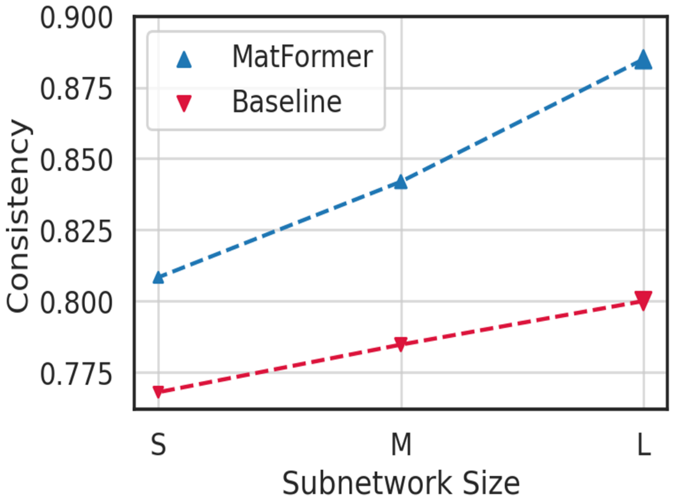
MatFormer : 23.0528 * N ^ -0.1407 + 1 / D + 1.4352

Baseline : 22.7879 * N ^ -0.1414 + 1 / D + 1.4973

Where N = N(Non-Embedding Parameters) and D = N(Training Tokens)

Above laws hold for all trained granularities: XL, L, M, S!

Language Modeling: Consistency for 2.6B XL model



***Consistency**: accuracy of smaller models (S, M, L) when output of XL model is the ground truth*

Why care about consistency?
Techniques like Speculative Decoding becomes more efficient with more consistent models

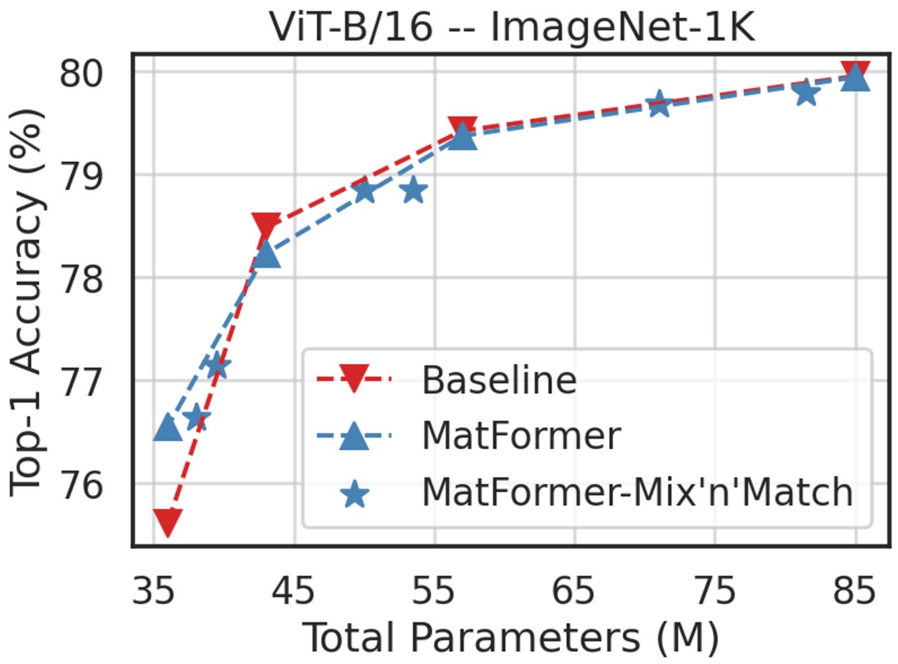
Speculative Decoding	LAMBADA	TriviaQA
Baseline	1.10×	1.08×
MatLM	1.14×	1.11×
+ shared attention cache	1.16×	1.14×

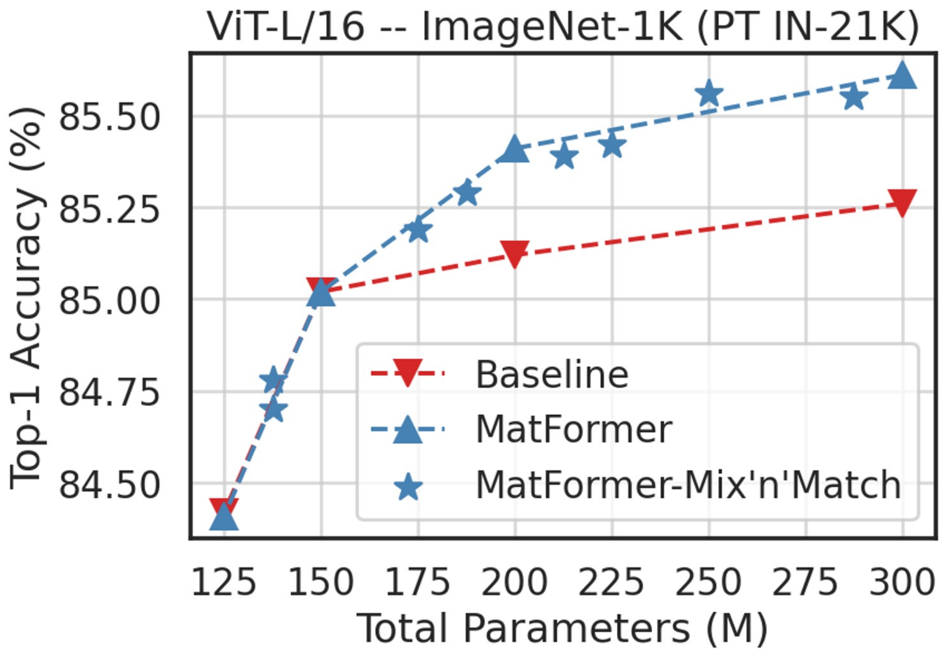
MatFormer subnetworks are significantly more consistent with the full model compared to vanilla baselines.

MatViT: MatFormer + ViT

- Generalized formulation translating to ViT
- Works for across model sizes for both pre-training and fine-tuning
- Enables accurate adaptive encoders for classification
    - Spans all of the space with Mix’n’Match (and potentially routing)
- Enables accurate adaptive query encoders for retrieval
    - Use the largest model for Index building
    - Leverage smaller query encoders during inference based on the constraints
    - This requires aligned training/distillation for baseline models to work

MatViT: Classification





All the ★ are for “free” during inference – *they were never optimized for.*

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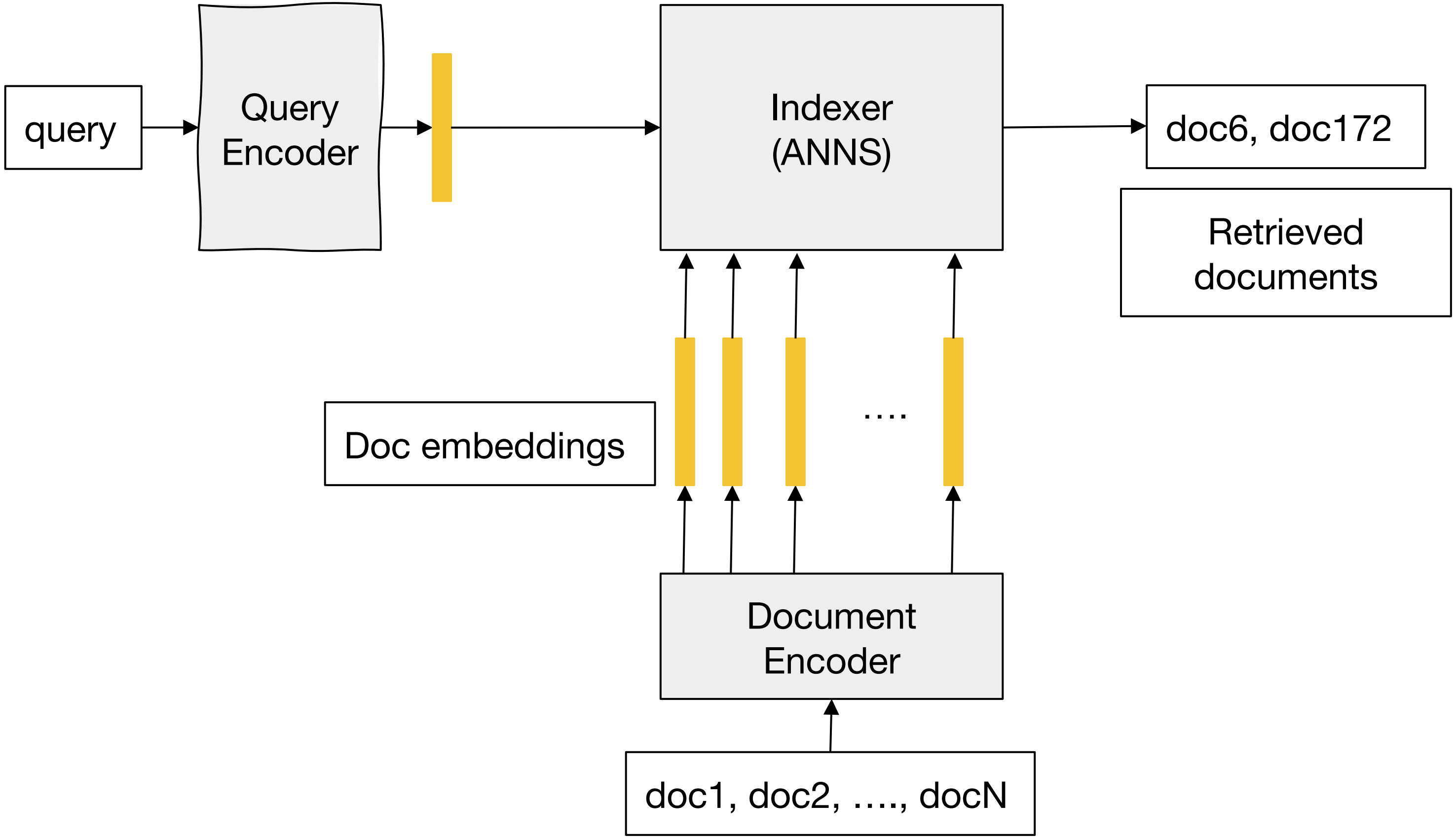
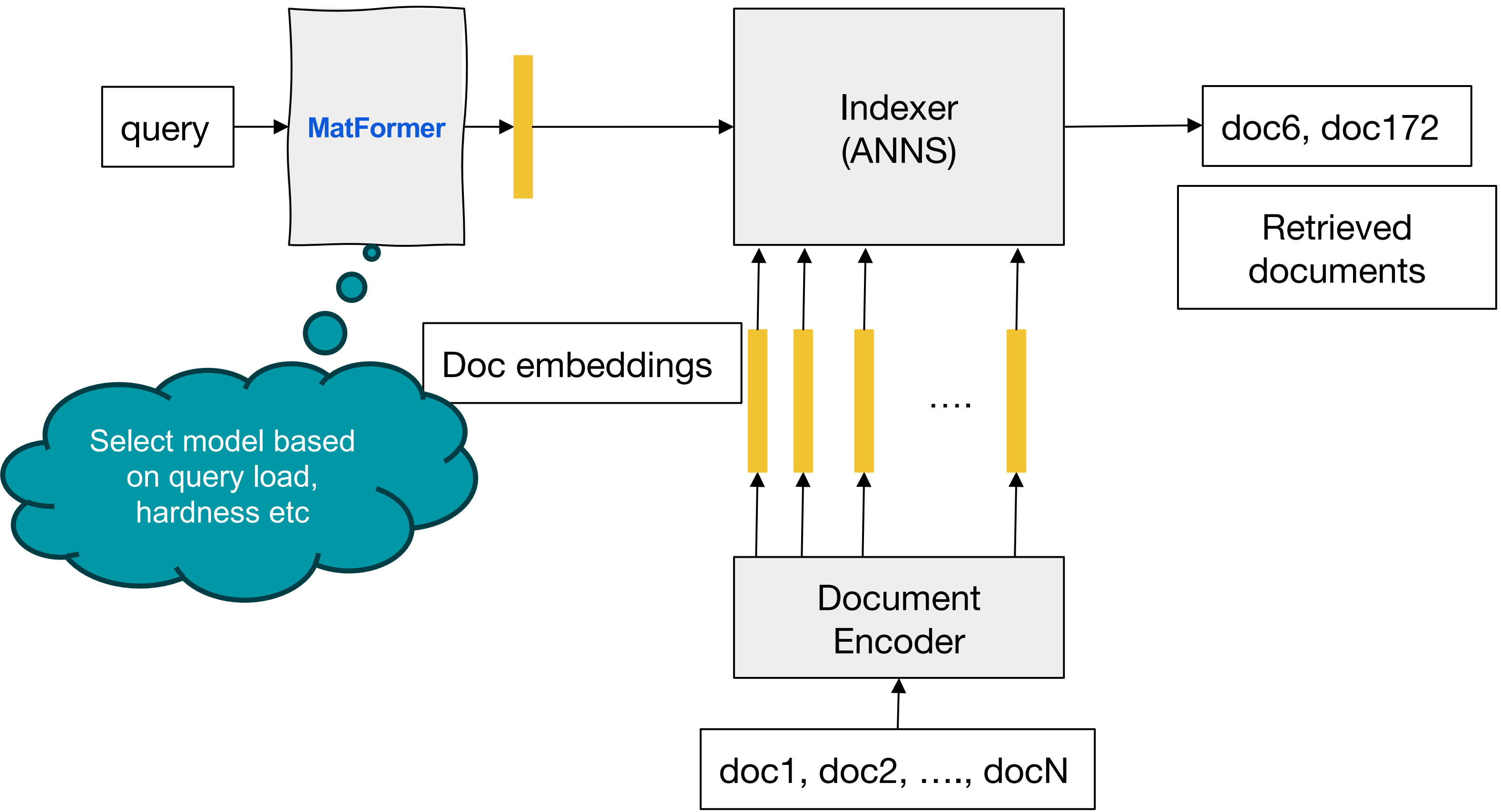
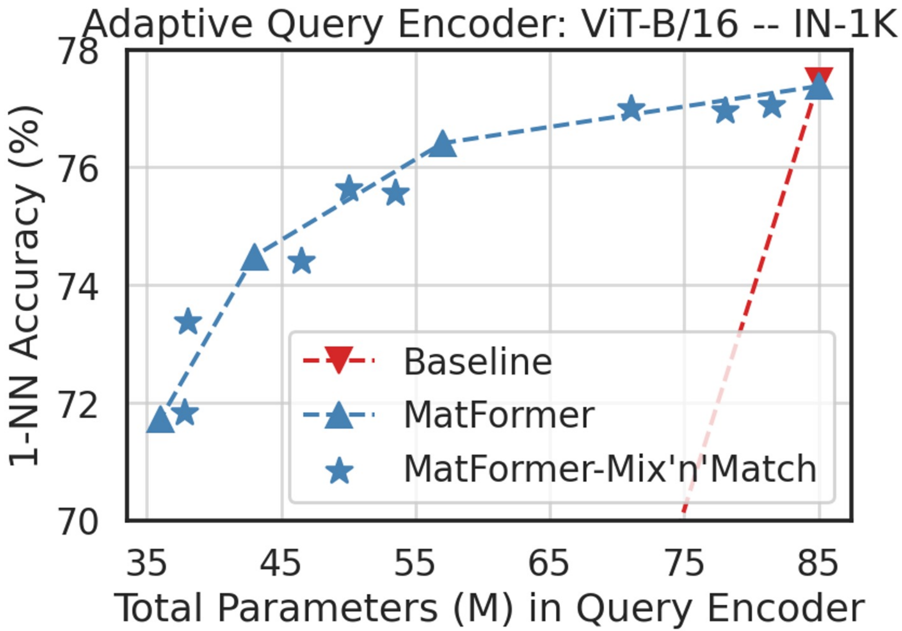
Semantic Search: Dual Encoder Models

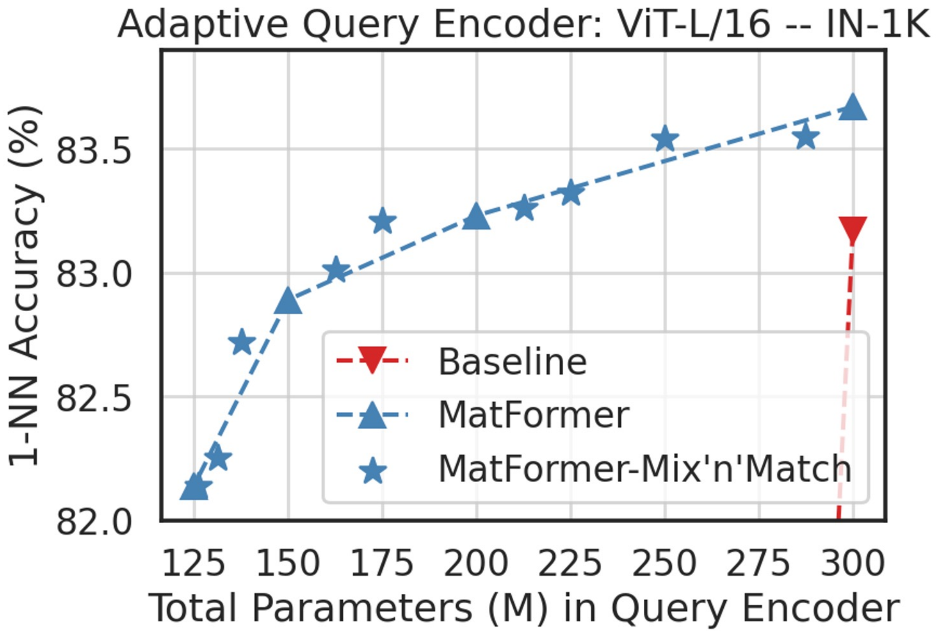


Semantic Search: Flexible Dual Encoder Model



MatViT: Adaptive Retrieval (Index built w/ largest model)





All the ★ are for “free” during inference & preserve metric space.

L/16 pretrained on IN-21K

MatFormer + ViT-B/16: Cross-consistent Retrieval

1-NN accuracy (%) with varying index and query encoder sizes from MatViT-B/16
(Baseline numbers): Rest are near Random

Index↓/Query→	36M	43M	57M	85M
36M	**72.42%** (71.44%)	74.31%	75.33%	76.26%
43M	72.30%	**74.71%** (74.90%)	75.93%	76.69%
57M	72.12%	74.71%	**76.44%** (76.58%)	77.19%
85M	71.71%	74.48%	76.40%	**77.40%** (77.46%)

Adaptive Query Encoders for Retrieval

Summary and Future Work

- Matformer: nested substructure for elastic inference
- Training: joint optimization of a few granularities
- MatLM: Matformer Language Model
  - 2.6B scale models with same pplx and evals as independently trained baselines
  - Consistency: gains over speculative decoding
- MatVIT: Matformer Vision Transformer
  - ViT-L/16 scale models, similar performance as independently trained baselines
  - Adaptive retrieval

Future Work:

- Further investigation of scaling laws
- Better training algorithms
- Practical deployment of a truly elastic system