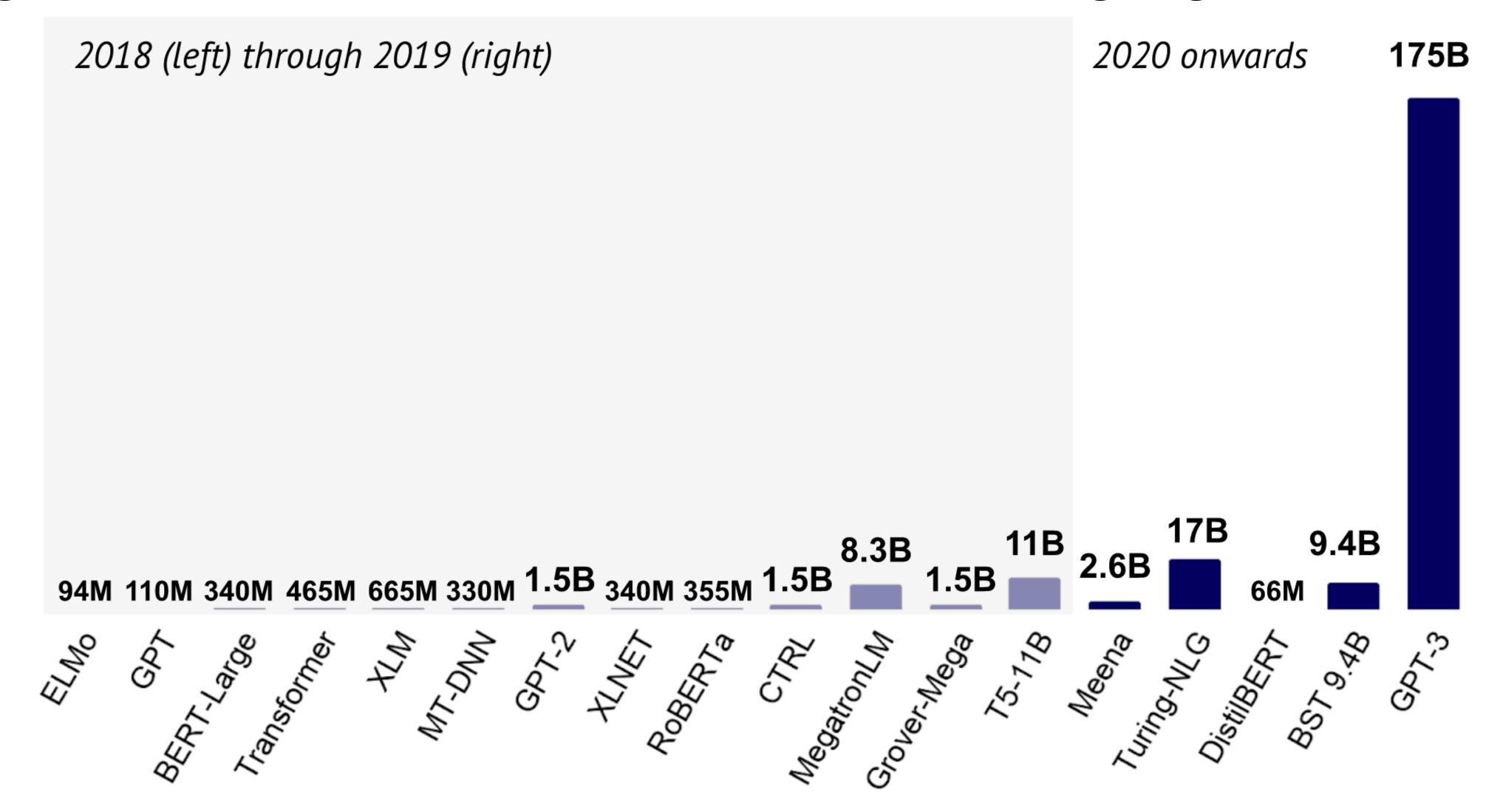
# Large Product Key Memory for Pretrained Language Models

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## Recent NLP Trends



# Decoupling Parameters & Performance

Model	# Layers	# Params	Inference Speed (batch/sec)	
BERT <sub>BASE</sub>	12	110M	79.8	
BERT <sub>BASE</sub> +PKM	12	506M	61.4	
BERT <sub>BASE</sub> +ResM	12	<b>515M</b>	<b>59.3</b>	
BERT <sub>LARGE</sub>	24	340M	43.1	
BERT <sub>LARGE</sub> +PKM	24	860M	37.2	
BERT <sub>LARGE</sub> +ResM	24	876M	36.1	

# Product Key Memory

#### Large Product Key Memory for Pretrained Language Models

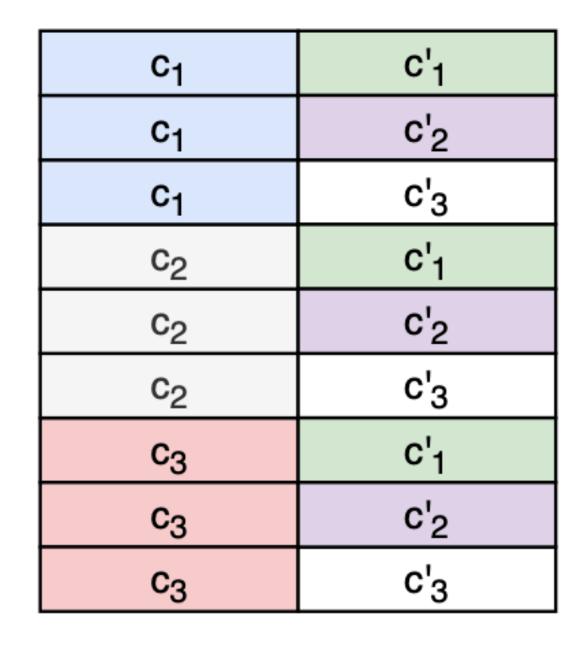
sub-key set 1

c <sub>1</sub>
$c_2$
c <sub>3</sub>

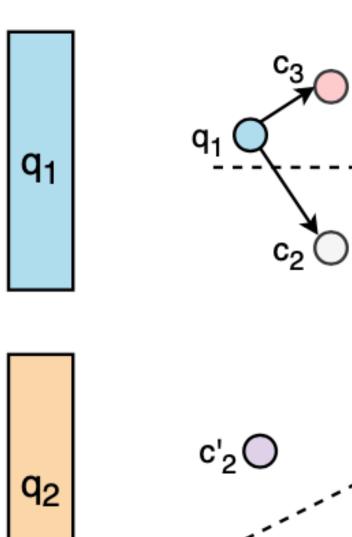
sub-key set 2

c' <sub>1</sub>
c' <sub>2</sub>
c' <sub>3</sub>

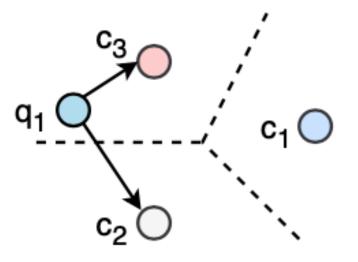
product keys

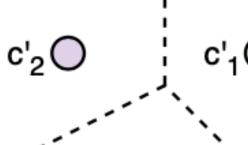


query



sub-key retrieval





 $k^2$  candidate keys

c <sub>2</sub>	C' <sub>1</sub>
c <sub>2</sub>	c' <sub>3</sub>
c <sub>3</sub>	c' <sub>1</sub>
c <sub>3</sub>	c' <sub>3</sub>

key selection

c <sub>2</sub>	c' <sub>1</sub>
c <sub>3</sub>	c' <sub>1</sub>

k selected keys

## Product Key Memory: Pseudo Code Large Product Key Memory for Pretrained Language Models

```
import torch
import torch nn as nn
import torch.nn.functional as F
def product_key_memory(query, dim, d_model, d_query, n_head):
  b , t , _ , h = query shape , n_head
  query = nn.Linear(d_model,d_query)(query)
  query = nn.Dropout(self.MaskedBatchNorm(query))
  query_list = query_chunk(2, dim = -1)
  query = torch.stack(query_list).reshape(2,b,t,h,-1)
 #self.key = nn.parameters(),
  weight = torch.matmul(query_list,self.key,transpose_a = True)
  scores, indices = weight.topk(k=self.topk, dim=-1)
  scores = F_ssoftmax(scores,dim = -1) #normalize
  top_k = sorted(dict((indices,scores)).items(), key=lambda x: x[1],reverse=True)[:10]
  top_k_indice = [indice for indice,score in top_k]
  out = nn.EmbeddingBag(n_key**2,dim,mode='sum')(top_k_indice)
  return nn.Dropout(out)
```

## PKM Performance

	Memory			MLM			
Model	MU (4L/8L) (%)	$KL_u$ (4L/8L)	KL <sub>w</sub> (4L/8L)	WT-2 (ppl)	WT-103 (ppl)	PG-19 (ppl)	
(a) BERT <sub>BASE</sub> <sup>†</sup> (b) +500k steps	-	<b>-</b>	-	3.49 3.40	3.86 3.72	6.18 5.88	
(c) +PKM (d) +ResM (e) +Init +PKM (f) +Init +ResM		1.62/0.89 1.50/0.71 0.53/0.69 <b>0.45/0.46</b>	1.99/1.13 1.80/0.92 0.68/0.88 <b>0.58/0.60</b>	3.26 3.26 3.14 3.10	3.39 3.36 3.26 3.20	5.53 5.45 5.22 <b>5.14</b>	

# Catastrophic Drift

	QA			GLUE	3		
Model	SQuAD 1.1	MNLI-(m/mm)	QQP	QNLI	SST-2	CoLA	Avg
	(EM/F1)	(Acc)	(Acc)	(Acc)	(Acc)	(Matt)	-
(a) BERT <sub>BASE</sub> <sup>†</sup>	82.7/89.8	84.3/84.5	91.0	89.3	92.8	60.8	83.8
(b) +500k steps	83.3/90.1	84.8/84.9	91.2	89.2	92.4	61.4	84.0
(c) +PKM	81.9/89.1	84.4/85.0	91.1	89.0	93.6	59.7	83.8
(d) +ResM	81.5/89.4	84.6/84.8	91.0	88.2	93.2	62.8	84.1
(e) +Init +PKM	83.8/90.6	85.8/85.6	91.2	90.0	93.6	63.6	85.0
(f) +Init +ResM	83.9/90.8	86.0/85.8	91.4	90.4	94.0	64.1	85.3
(g) BERT <sub>BASE</sub> *	81.1/88.5	83.9/84.4	91.0	88.4	92.9	59.8	83.4
(h) BERT <sub>LARGE</sub> *	83.3/90.6	86.2/86.1	91.4	90.4	93.8	64.1	85.3

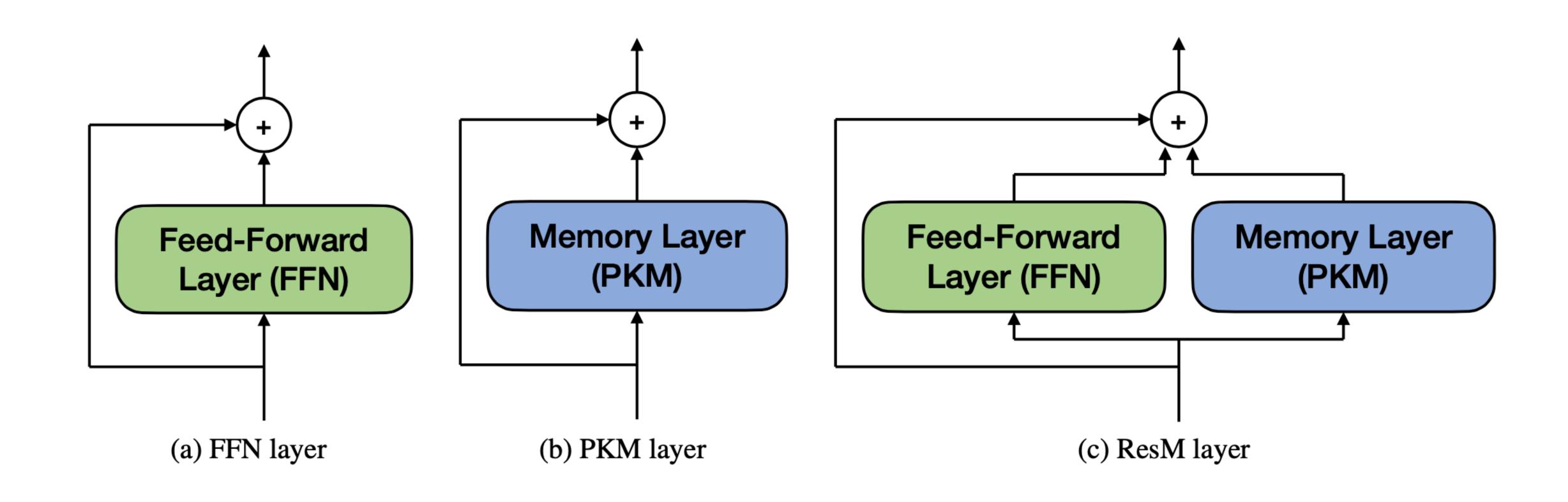
## Solutions

Large Product Key Memory for Pretrained Language Models

Initialization from Pretrained Weights

Residual Memory Layer

### Model Architecture



## ResM Performance

QA			GLUE					
Model	SQuAD 1.1 (EM/F1)	MNLI-(m/mm) (Acc)	QQP (Acc)	QNLI (Acc)	SST-2 (Acc)	CoLA (Matt)	Avg -	
(a) BERT <sub>BASE</sub> <sup>†</sup> (b) +500k steps	82.7/89.8	84.3/84.5	91.0	89.3	92.8	60.8	83.8	
	83.3/90.1	84.8/84.9	91.2	89.2	92.4	61.4	84.0	
(c) +PKM	81.9/89.1	84.4/85.0	91.1	89.0	93.6	59.7	83.8	
(d) +ResM	81.5/89.4	84.6/84.8	91.0	88.2	93.6	62.8	84.1	
(e) +Init +PKM	83.8/90.6	85.8/85.6	91.2	90.0	93.6	63.6	85.0	
(f) +Init +ResM	<b>83.9/90.8</b>	<b>86.0/85.8</b>	<b>91.4</b>	<b>90.4</b>	<b>94.0</b>	<b>64.1</b>	<b>85.3</b>	
(g) BERT <sub>BASE</sub> * (h) BERT <sub>LARGE</sub> *	81.1/88.5	83.9/84.4	91.0	88.4	92.9	59.8	83.4	
	83.3/90.6	86.2/86.1	91.4	90.4	93.8	64.1	85.3	

# Further Implications

	MLM	QA	QA GL	
Model	PG-19	SQuAD 1.1	MNLI-m	SST-2
	(ppl)	(EM/F1)	(Acc)	(Acc)
DistilBERT*	20.61	77.4/85.7	82.0	91.6
+Init +ResM	5.75	80.4/88.3	84.1	93.3
BERT <sub>BASE</sub> *	11.82	81.1/88.5	83.9	92.9