Pretrained Models

Collective Machine Intelligence

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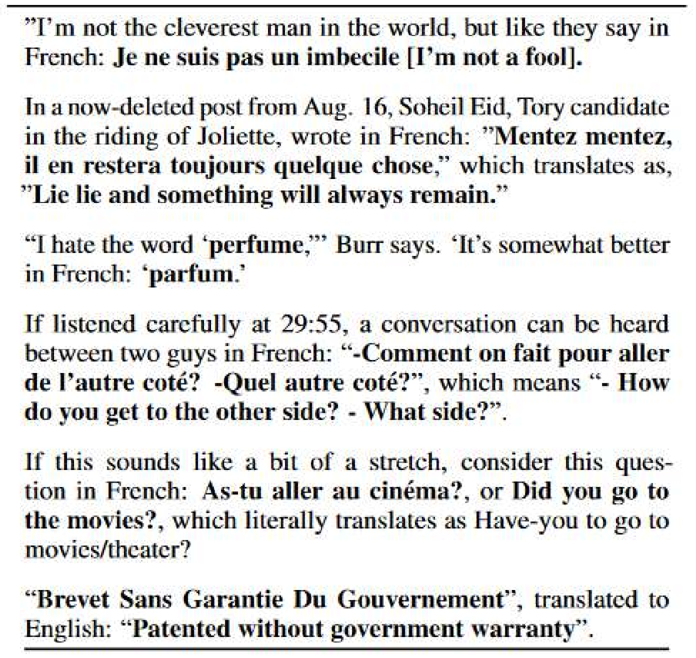
Outline

- **Data**: quality, evaluation, scaling laws
- **Models**: Vision and Vision-Language Transformers
- **Efficient Finetuning**: Distillation, LoRA, Prompt Tuning
- **Research**: Model patching, model editing, explaining ICL

Large-Scale Pretraining

Training on a Web-Scale

- We have a very bad intuition about how much diversity there is in web-scale data
  - In general, much more diversity than we expect
  - There are examples of general tasks such as translation
- language provides a flexible way to specify tasks, inputs, and outputs all as a sequence of symbols
  - How do we use language to achieve few-shot and zero-shot learning?



”I’m not the cleverest man in the world, but like they say in French: **Je ne suis pas un imbecile [I’m not a fool].**

In a now-deleted post from Aug. 16, Soheil Eid, Tory candidate in the riding of Joliette, wrote in French: **”Mentez mentez, il en restera toujours quelque chose,”** which translates as, **”Lie lie and something will always remain.”**

“I hate the word **‘perfume,’**” Burr says. ‘It’s somewhat better in French: **‘parfum.’**

If listened carefully at 29:55, a conversation can be heard between two guys in French: “**-Comment on fait pour aller de l’autre coté? -Quel autre coté?**”, which means “**- How do you get to the other side? - What side?**”.

If this sounds like a bit of a stretch, consider this question in French: **As-tu aller au cinéma?**, or **Did you go to the movies?**, which literally translates as Have-you to go to movies/theater?

“**Brevet Sans Garantie Du Gouvernement**”, translated to English: “**Patented without government warranty**”.

Table 1. Examples of naturally occurring demonstrations of English to French and French to English translation found throughout the WebText training set.

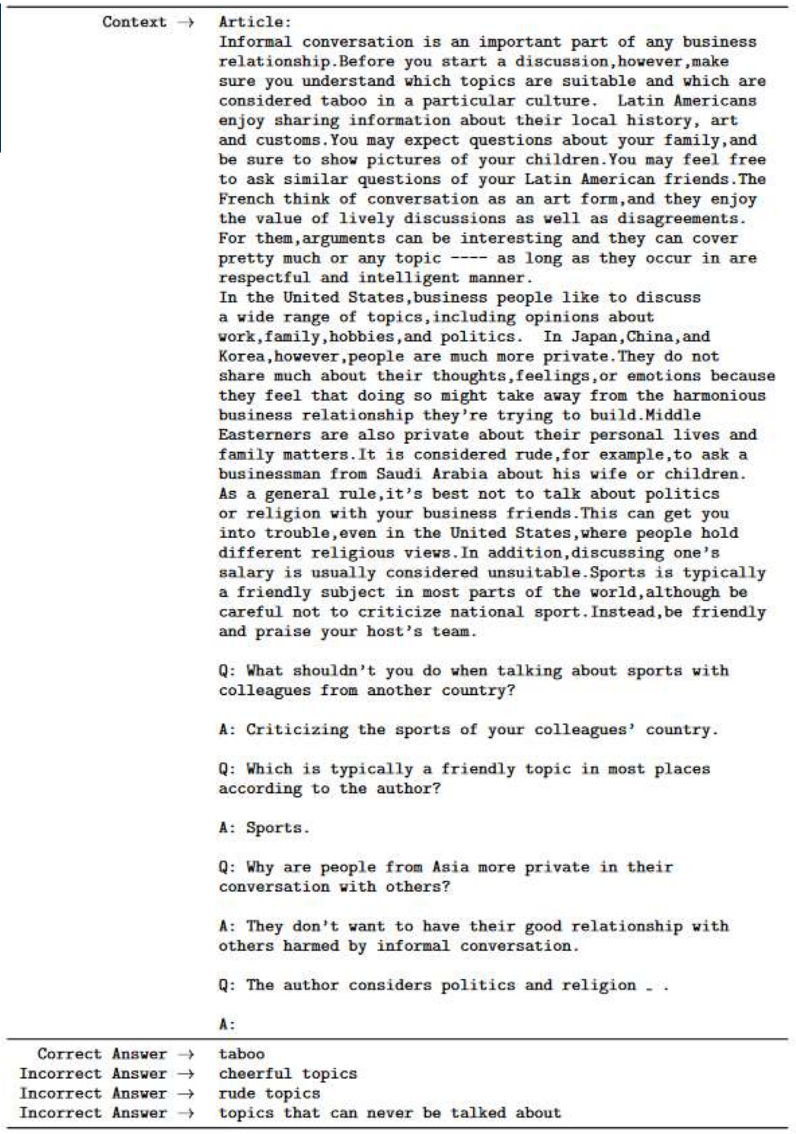
A. Radford et al. “Language Models Are Unsupervised Multitask Learners.”

Few-Shot and Zero-Shot Learning

Given a large pretrained language model

- **In-Context-Learning/Prompting**: at inference time we give a description of the task, (optionally) followed by a sequence of examples
    - No weights are updated
- **Few-Shot**: the model is given a few samples of the task as conditioning
- **One-Shot**: a single example
- **Zero-Shot**: only the task description is given

Examples

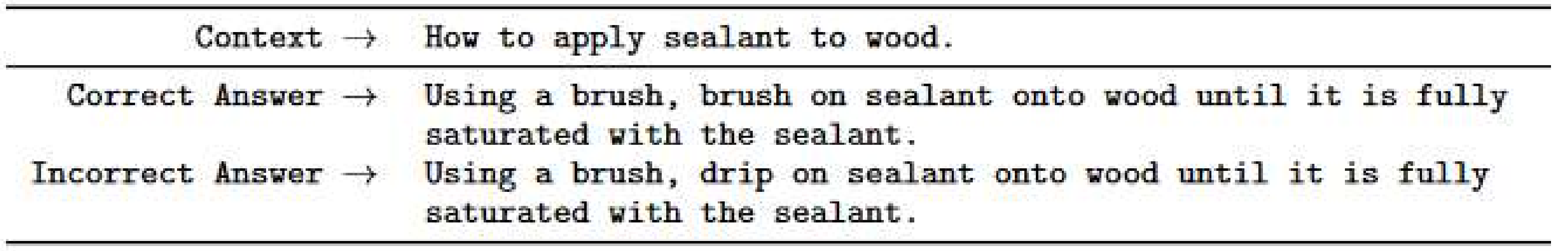


```
Context →  Article:
           Informal conversation is an important part of any business
           relationship.Before you start a discussion,however,make
           sure you understand which topics are suitable and which are
           considered taboo in a particular culture.  Latin Americans
           enjoy sharing information about their local history, art
           and customs.You may expect questions about your family,and
           be sure to show pictures of your children.You may feel free
           to ask similar questions of your Latin American friends.The
           French think of conversation as an art form,and they enjoy
           the value of lively discussions as well as disagreements.
           For them,arguments can be interesting and they can cover
           pretty much or any topic ---- as long as they occur in are
           respectful and intelligent manner.
           In the United States,business people like to discuss
           a wide range of topics,including opinions about
           work,family,hobbies,and politics.  In Japan,China,and
           Korea,however,people are much more private.They do not
           share much about their thoughts,feelings,or emotions because
           they feel that doing so might take away from the harmonious
           business relationship they're trying to build.Middle
           Easterners are also private about their personal lives and
           family matters.It is considered rude,for example,to ask a
           businessman from Saudi Arabia about his wife or children.
           As a general rule,it's best not to talk about politics
           or religion with your business friends.This can get you
           into trouble,even in the United States,where people hold
           different religious views.In addition,discussing one's
           salary is usually considered unsuitable.Sports is typically
           a friendly subject in most parts of the world,although be
           careful not to criticize national sport.Instead,be friendly
           and praise your host's team.

           Q: What shouldn't you do when talking about sports with
           colleagues from another country?

           A: Criticizing the sports of your colleagues' country.

           Q: Which is typically a friendly topic in most places
           according to the author?

           A: Sports.

           Q: Why are people from Asia more private in their
           conversation with others?

           A: They don't want to have their good relationship with
           others harmed by informal conversation.

           Q: The author considers politics and religion _ .

           A:

  Correct Answer →   taboo
Incorrect Answer →   cheerful topics
Incorrect Answer →   rude topics
Incorrect Answer →   topics that can never be talked about
```

Figure G.1: Formatted dataset example for RACE-h. When predicting, we normalize by the unconditional probability of each answer.

T. Brown et al. "Language Models Are Few-Shot Learners." NeurIPS 2020

Examples of Prompts



Context →	How to apply sealant to wood.
Correct Answer →	Using a brush, brush on sealant onto wood until it is fully saturated with the sealant.
Incorrect Answer →	Using a brush, drip on sealant onto wood until it is fully saturated with the sealant.

Figure G.4: Formatted dataset example for PIQA

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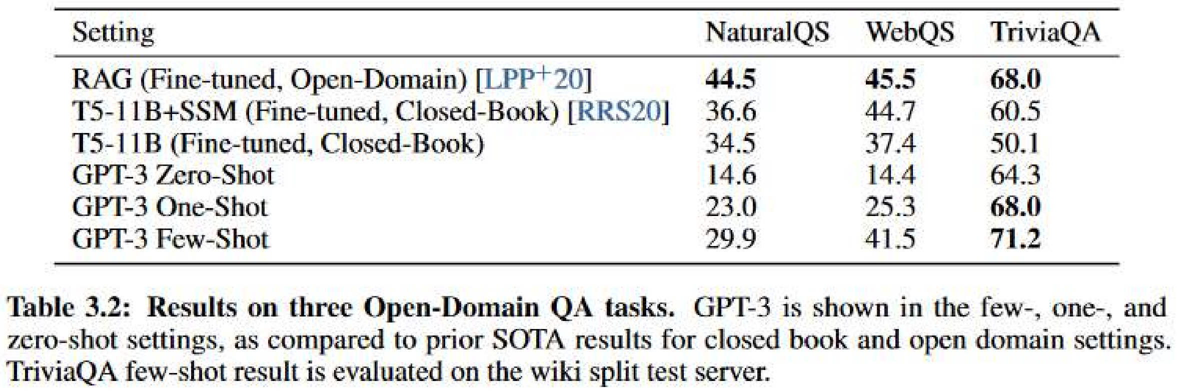
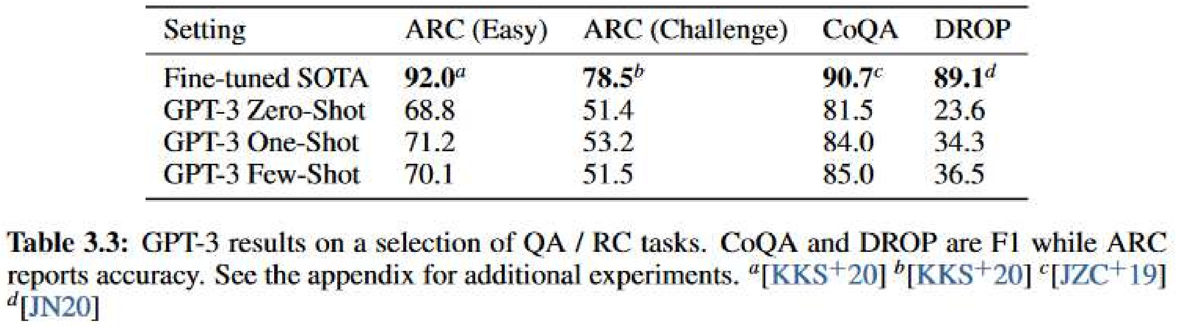
LLMs are Few-Shot Learners



Setting	NaturalQS	WebQS	TriviaQA
RAG (Fine-tuned, Open-Domain) [LPP+20]	**44.5**	**45.5**	**68.0**
T5-11B+SSM (Fine-tuned, Closed-Book) [RRS20]	36.6	44.7	60.5
T5-11B (Fine-tuned, Closed-Book)	34.5	37.4	50.1
GPT-3 Zero-Shot	14.6	14.4	64.3
GPT-3 One-Shot	23.0	25.3	**68.0**
GPT-3 Few-Shot	29.9	41.5	**71.2**

Table 3.2: Results on three Open-Domain QA tasks. GPT-3 is shown in the few-, one-, and zero-shot settings, as compared to prior SOTA results for closed book and open domain settings. TriviaQA few-shot result is evaluated on the wiki split test server.



Setting	ARC (Easy)	ARC (Challenge)	CoQA	DROP
Fine-tuned SOTA	**92.0**[a]	**78.5**[b]	**90.7**[c]	**89.1**[d]
GPT-3 Zero-Shot	68.8	51.4	81.5	23.6
GPT-3 One-Shot	71.2	53.2	84.0	34.3
GPT-3 Few-Shot	70.1	51.5	85.0	36.5

Table 3.3: GPT-3 results on a selection of QA / RC tasks. CoQA and DROP are F1 while ARC reports accuracy. See the appendix for additional experiments. [a][KKS+20] [b][KKS+20] [c][JZC+19] [d][JN20]

T. Brown et al. "Language Models Are Few-Shot Learners." NeurIPS 2020

Challenges

- Prompting requires rethinking the adaptation and finetuning of models
- It’s hard to evaluate LLMs zero-shot ability
  - How can we ensure that the task is really unseen?
- Still hard to control the model or estimate uncertainty

Challenges in the Evaluation

- Github CoPilot memorized the solution of many programming challenges
- Example: Project Euler #14
  - A simple problem about the convergence of Collatz sequences

How to get your solution

- Add a comment with the link to project euler
- *# https://projecteuler.net/problem=14*
- Press tab or enter until the code is complete. Copilot will write the full solution

```python
# https://projecteuler.net/problem=14

# imports
import time

# Measure runtime
start = time.time()

# Variables
longest_chain = 0
longest_chain_start = 0

# Functions
def collatz(n):
    chain = 1
    while n != 1:
        if n % 2 == 0:
            n = n/2
            chain += 1
        else:
            n = 3*n + 1
            chain += 1
    return chain


# Main
for i in range(1, 1000000):
    chain = collatz(i)
    if chain > longest_chain:
        longest_chain = chain
        longest_chain_start = i

print(longest_chain_start)

# Print runtime
print("--- %.2f seconds ---" %(time.time() - start))
```

Data and Scaling Laws

Model Scale

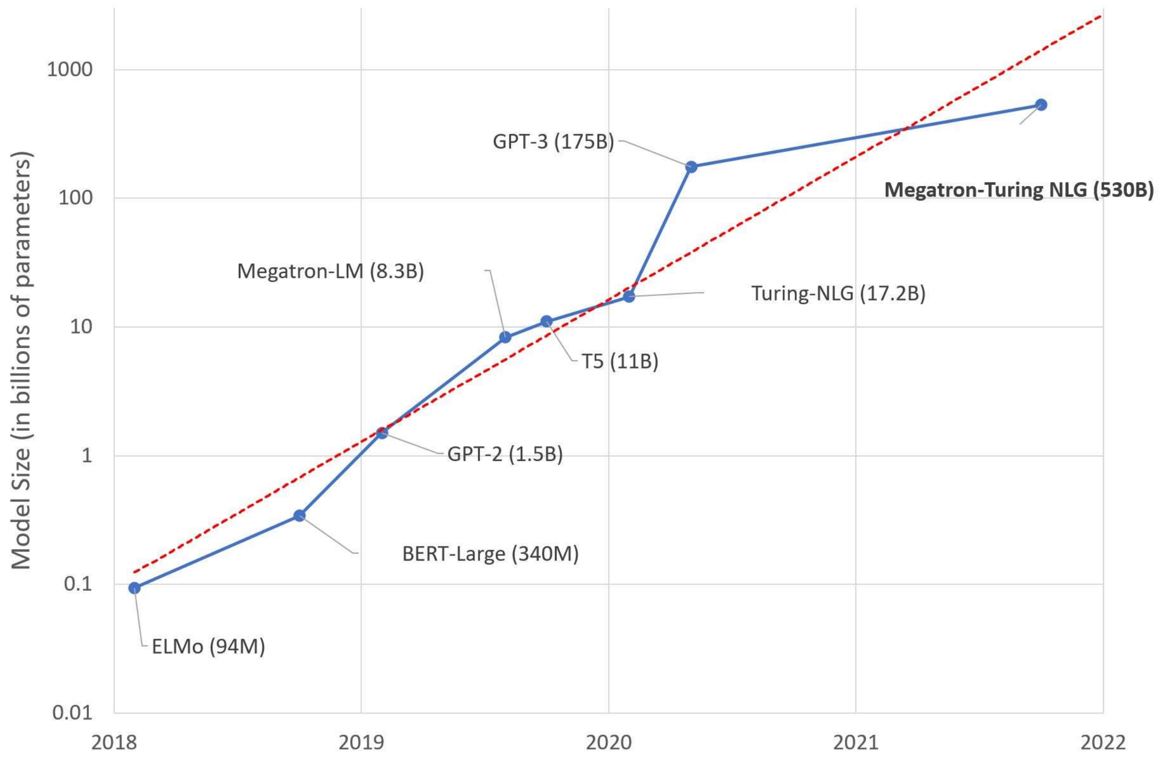


image from https://huggingface.co/blog/large-language-models

Training Large (Huge) Models

Training large models is very expensive

- You can train a single run (it cost M$)
- You would like to know the cost in advance, whether the performance improvements are worth the cost

Problems:

- How do we do model selection?
- How do we choose the model size?
- How much data do we need?
- What error will we get?

Model Selection

- You can’t do it. A training is a single run
- If models become unstable recover from previous checkpoints
- Needs to account for machine failures (the model is trained on a cluster)

Chinchilla Scaling Law

- **Chinchilla Scaling Law**: an empirical law that determines the loss given
  - **N**: number of parameters of the model
  - **D**: number of tokens in the dataset
  - Three components: model error, data error, irreducible loss

$$L(N, D) = \underbrace{\frac{406.4}{N^{0.34}}}_{\text{finite model}} + \underbrace{\frac{410.7}{D^{0.28}}}_{\text{finite data}} + \underbrace{1.69}_{\text{irreducible}}$$

Compute-Optimal Models

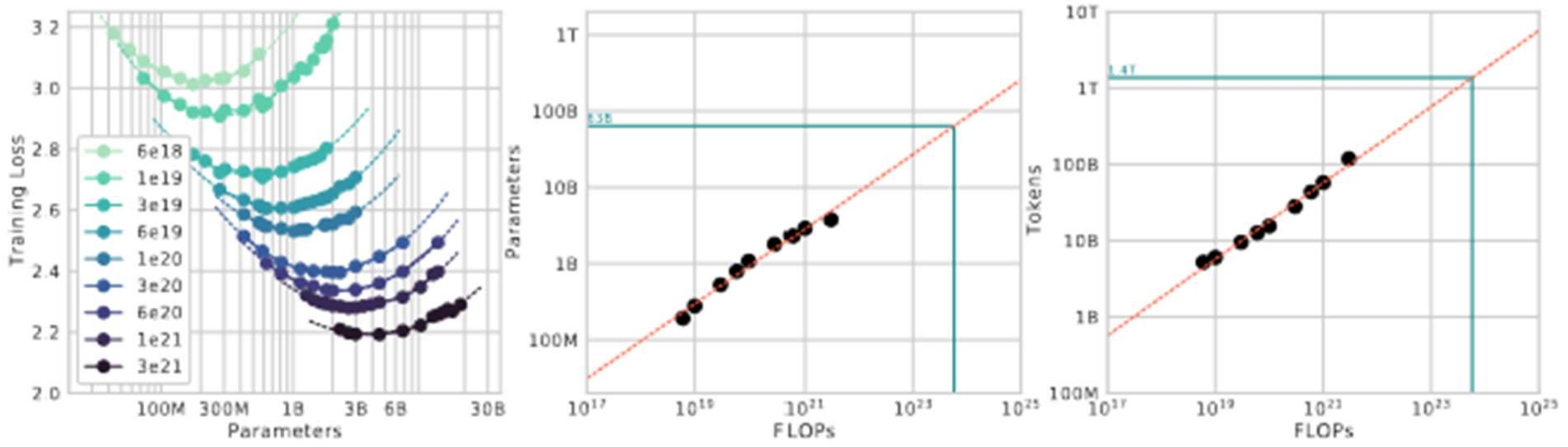


Figure 3 | IsoFLOP curves. For various model sizes, we choose the number of training tokens such that the final FLOPs is a constant. The cosine cycle length is set to match the target FLOP count. We find a clear valley in loss, meaning that for a given FLOP budget there is an optimal model to train (**left**). Using the location of these valleys, we project optimal model size and number of tokens for larger models (**center** and **right**). In green, we show the estimated number of parameters and tokens for an *optimal* model trained with the compute budget of *Gopher*.

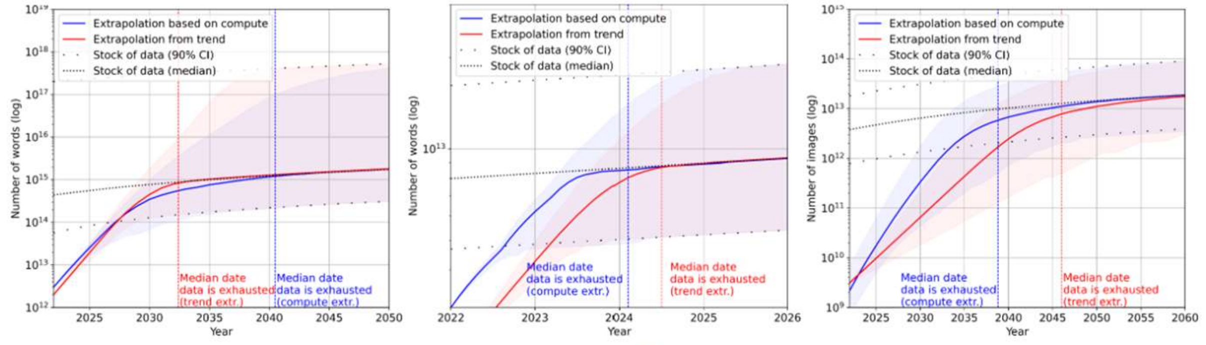
Compute-Optimal Models

- Larger models are not always better, you also need larger data
- Given a fixed computational budget and a dataset, you can find the optimal model size
- The optimality is wrt to the loss and training cost.
  - Inference cost is ignored and it can be high due to the large model size suggested by the Eq.
- Unclear if the scaling law will hold for larger models

How much data do we have?

If the trend continues

- **high-quality language data** will be exhausted soon; likely before 2026.
- **low-quality** language data and image data will be exhausted only much later; between 2030 and 2050 (for low-quality language) and between 2030 and 2060 (for images).

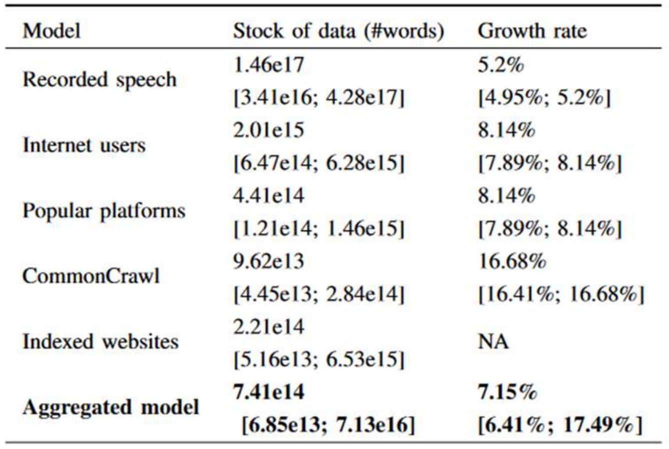


(a) Projections for low-quality language data

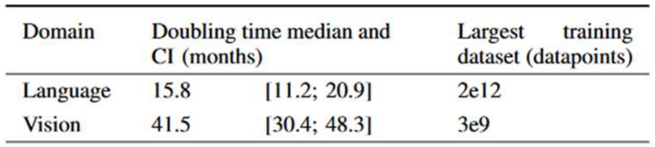
(b) Projections for high-quality language data

(c) Projections for vision data

Fig. 1: Projections of data usage. Each graph shows two extrapolations of data usage, one from past trends and one from compute availability estimations plus scaling laws. Both projections are constrained to be lower than the estimated data stock. In all three cases, this constraint causes a slowdown in data usage growth.

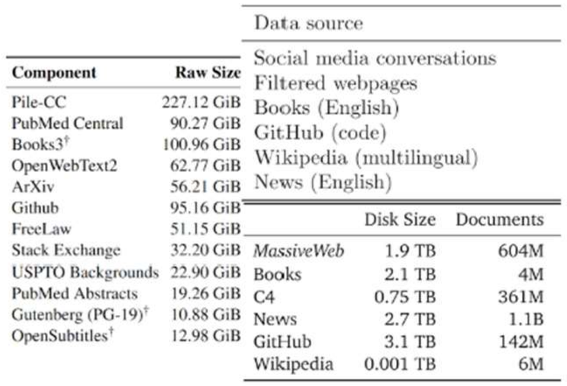


Model	Stock of data (#words)	Growth rate
Recorded speech	1.46e17 [3.41e16; 4.28e17]	5.2% [4.95%; 5.2%]
Internet users	2.01e15 [6.47e14; 6.28e15]	8.14% [7.89%; 8.14%]
Popular platforms	4.41e14 [1.21e14; 1.46e15]	8.14% [7.89%; 8.14%]
CommonCrawl	9.62e13 [4.45e13; 2.84e14]	16.68% [16.41%; 16.68%]
Indexed websites	2.21e14 [5.16e13; 6.53e15]	NA
Aggregated model	**7.41e14 [6.85e13; 7.13e16]**	**7.15% [6.41%; 17.49%]**



Domain	Doubling time median and CI (months)		Largest training dataset (datapoints)
Language	15.8	[11.2; 20.9]	2e12
Vision	41.5	[30.4; 48.3]	3e9

TABLE I: Trends in training dataset size for vision and language models.

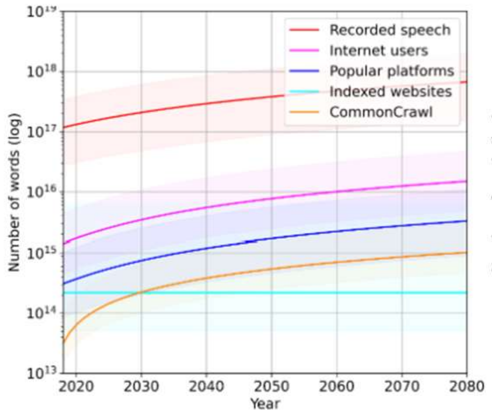


Component	Raw Size
Pile-CC	227.12 GiB
PubMed Central	90.27 GiB
Books3[†]	100.96 GiB
OpenWebText2	62.77 GiB
ArXiv	56.21 GiB
Github	95.16 GiB
FreeLaw	51.15 GiB
Stack Exchange	32.20 GiB
USPTO Backgrounds	22.90 GiB
PubMed Abstracts	19.26 GiB
Gutenberg (PG-19)[†]	10.88 GiB
OpenSubtitles[†]	12.98 GiB

Data source
Social media conversations
Filtered webpages
Books (English)
GitHub (code)
Wikipedia (multilingual)
News (English)

	Disk Size	Documents
MassiveWeb	1.9 TB	604M
Books	2.1 TB	4M
C4	0.75 TB	361M
News	2.7 TB	1.1B
GitHub	3.1 TB	142M
Wikipedia	0.001 TB	6M

(a) Composition of high-quality datasets: The Pile (left), PaLM (top-right), MassiveText (bottom-right)



(a) Comparison of the different data stock models.

Vision Transformer

Attention

- $\text{MultiHead}(Q, K, V) = \text{Concat}(\text{ head }_1, \dots, \text{head }_h)W^O$
- $head_i \; = \text{Attention}\left(QW_i^Q, KW_i^K, VW_i^V\right)$
    - Transformers use multiple heads, each transformed by different linear projections
- $\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$
    - Scaled dot-product attention
    - Q query
    - K keys
    - V values

Vision Transformer

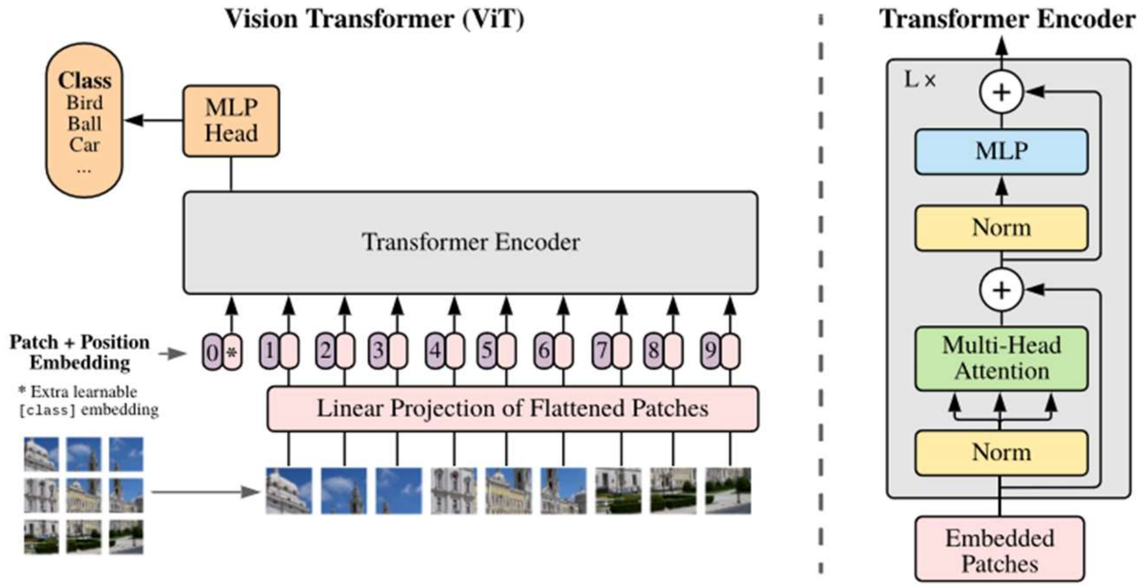


Figure 1: Model overview. We split an image into fixed-size patches, linearly embed each of them, add position embeddings, and feed the resulting sequence of vectors to a standard Transformer encoder. In order to perform classification, we use the standard approach of adding an extra learnable "classification token" to the sequence. The illustration of the Transformer encoder was inspired by Vaswani et al. (2017).

Embedding Image Patches

- Split images in 16x16 patches
- Add positional embedding
  - Learnable 1D embeddings
  - Needed because attention is invariant to the patch position
- Once we have the 1D embeddings, we can use the Transformer like we do for text

ViT Block

- MSA: Multiheaded Self-Attention
- LN: Layer Normalization
- GELU nonlinearity

- $\mathbf{z}_0 = \left[\mathbf{x}_{\text{class}}\, ; \mathbf{x}_p^1\mathbf{E}; \mathbf{x}_p^2\mathbf{E}; \cdots ; \mathbf{x}_p^N\mathbf{E}\right] + \mathbf{E}_{pos}$
- $\mathbf{z}'_\ell = \mathrm{MSA}\left(\mathrm{LN}(\mathbf{z}_{\ell-1})\right) + \mathbf{z}_{\ell-1},\ \ \ell = 1 \dots L$
- $\mathbf{z}_\ell = \mathrm{MLP}\left(\mathrm{LN}(\mathbf{z}'_\ell)\right) + \mathbf{z}'_\ell,\ \ \ell = 1 \dots L$
- $\mathbf{y} = \mathrm{LN}\left(\mathbf{z}_L^0\right)$

- $\mathbf{E} \in \mathbb{R}^{(P^2 \cdot C) \times D}, \mathbf{E}_{pos} \in \mathbb{R}^{(N+1) \times D}$
- $\mathbf{E}$ projects embedding into latent space
- Image HxWxC
- Patch P^2C (flattened patch)
- D latent size dimension
- $\mathbf{x}_{\text{class}}$ is a learned embedding and provides the final image representation at the last layer (equivalent to `BERT[class]` token)

Results

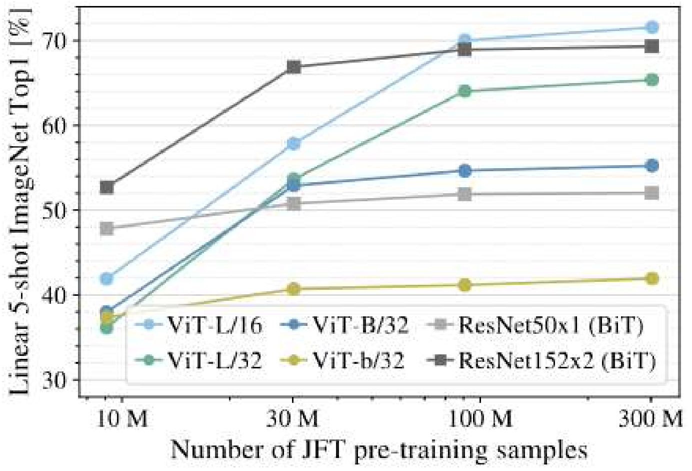


Figure 4: Linear few-shot evaluation on ImageNet versus pre-training size. ResNets perform better with smaller pre-training datasets but plateau sooner than ViT, which performs better with larger pre-training. ViT-b is ViT-B with all hidden dimensions halved.

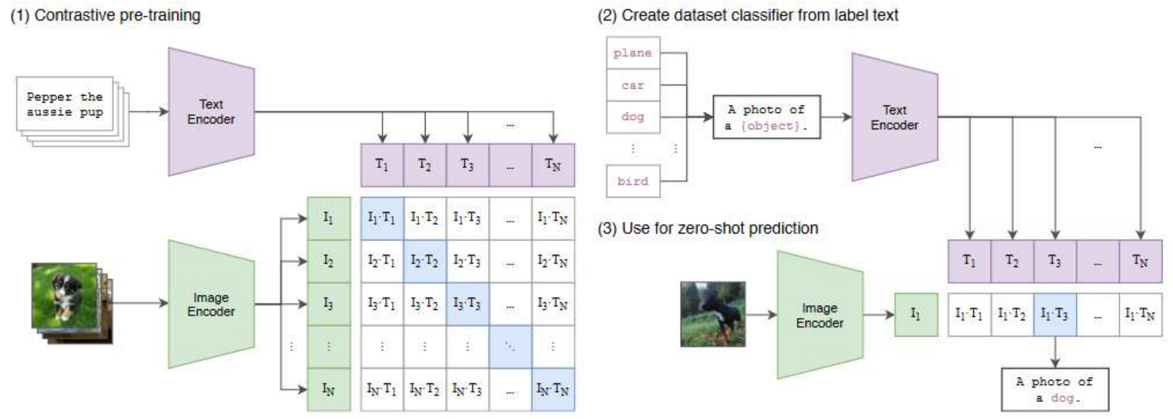
Vision-Language Models

Motivation

- With LLM we can do zero-shot training with prompting
- We want to exploit language to encode visual information
  - Language encodes a high-level understanding of images
  - We have lots of captioned images that provide much more information than using the image alone
- We need to combine vision and language models

Vision-Language Pretraining with CLIP

- **pre-training task:** learn to map text captions with visual images
- **zero-shot transfer**: natural language is used to reference learned visual concepts (or describe new ones)



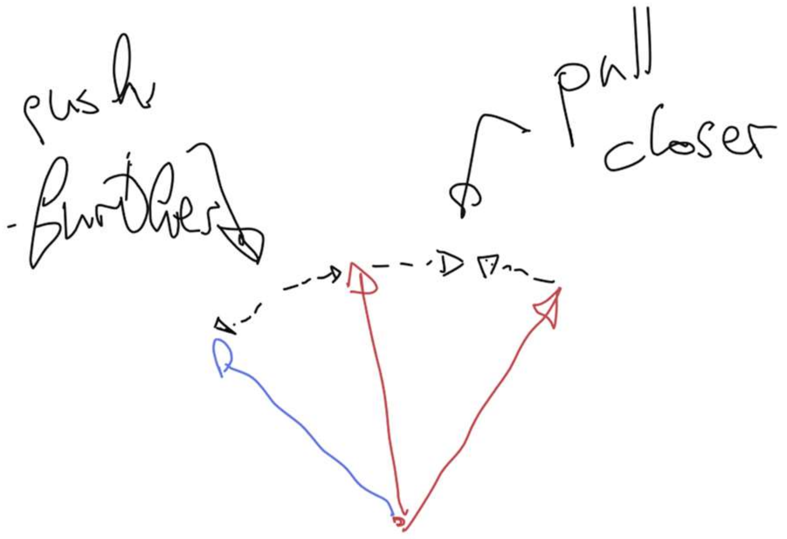
(1) Contrastive pre-training
Pepper the aussie pup
Text Encoder
Image Encoder
T1 T2 T3 ... TN
I1 I2 I3 ... IN
I1·T1 I1·T2 I1·T3 ... I1·TN
IN·T1 IN·T2 IN·T3 ... IN·TN
(2) Create dataset classifier from label text
plane
car
dog
bird
A photo of a {object}.
(3) Use for zero-shot prediction
A photo of a dog.

Figure 1. Summary of our approach. While standard image models jointly train an image feature extractor and a linear classifier to predict some label, CLIP jointly trains an image encoder and a text encoder to predict the correct pairings of a batch of (image, text) training examples. At test time the learned text encoder synthesizes a zero-shot linear classifier by embedding the names or descriptions of the target dataset's classes.

A. Radford et al. 2021. "Learning Transferable Visual Models From Natural Language Supervision."

Contrastive Learning

- **Objective**: learn a latent representation space that is semantically meaningful (for downstream tasks)
- **Example**: in a downstream classification problem, we would like the examples to be linearly separable
- **IDEA**: similar images are close to each other, diverse images are far
- **contrastive learning**: compare and contrast pairs of images during training to learn good representations

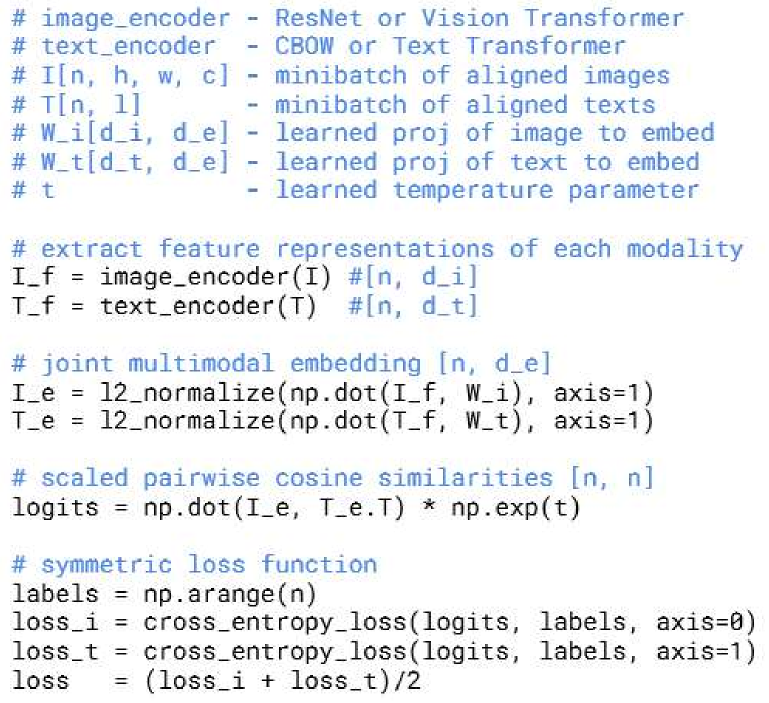


Contrastive Pretraining

- **Supervised training** is inefficient if we try to learn from <caption, image> pairs
  - There is too much diversity in the possible images and captions
  - It is very difficult to predict the exact image/captions of the current pair
- Solution: **contrastive training**
  - Given a batch of <caption, image> pairs, predict which text caption maps with which image among the NxN possibilites
  - Learns a multi-modal embedding space where text and images are aligned

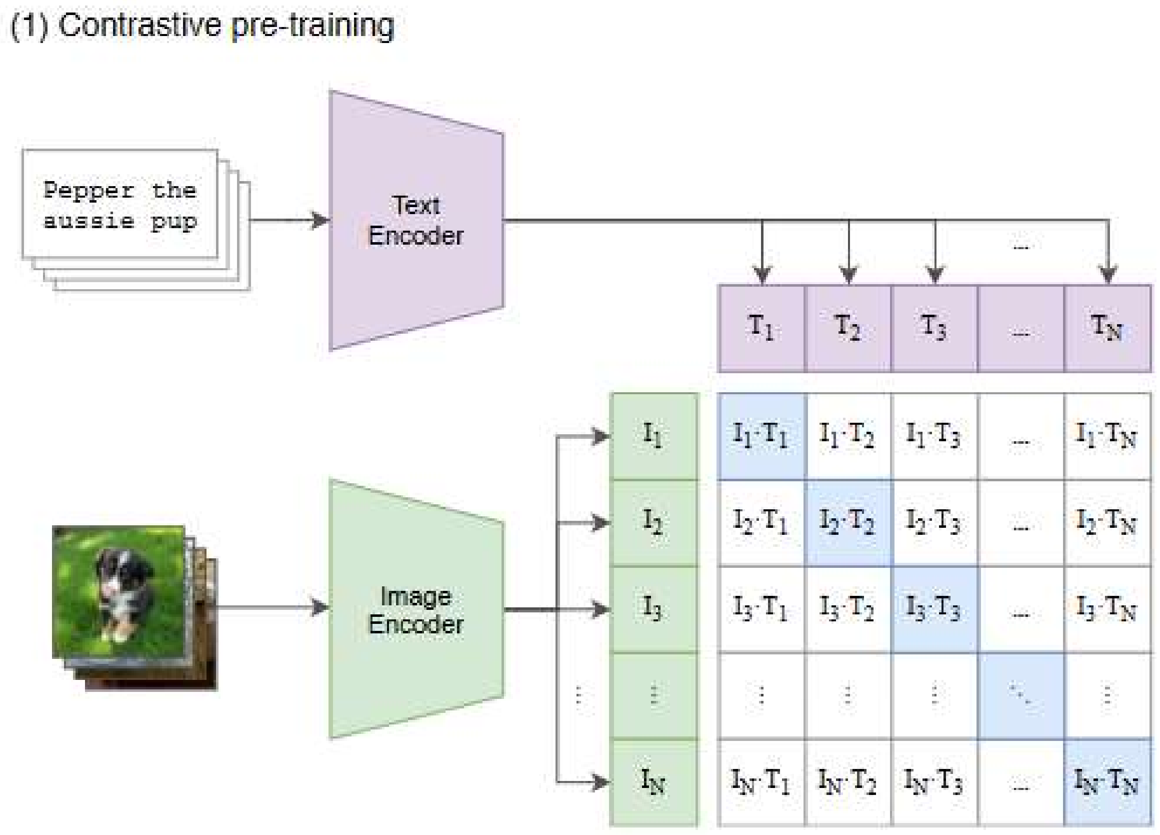
A. Radford et al. 2021. "Learning Transferable Visual Models From Natural Language Supervision."

CLIP Pretraining



```
# image_encoder - ResNet or Vision Transformer
# text_encoder  - CBOW or Text Transformer
# I[n, h, w, c] - minibatch of aligned images
# T[n, l]       - minibatch of aligned texts
# W_i[d_i, d_e] - learned proj of image to embed
# W_t[d_t, d_e] - learned proj of text to embed
# t             - learned temperature parameter

# extract feature representations of each modality
I_f = image_encoder(I) #[n, d_i]
T_f = text_encoder(T)  #[n, d_t]

# joint multimodal embedding [n, d_e]
I_e = l2_normalize(np.dot(I_f, W_i), axis=1)
T_e = l2_normalize(np.dot(T_f, W_t), axis=1)

# scaled pairwise cosine similarities [n, n]
logits = np.dot(I_e, T_e.T) * np.exp(t)

# symmetric loss function
labels = np.arange(n)
loss_i = cross_entropy_loss(logits, labels, axis=0)
loss_t = cross_entropy_loss(logits, labels, axis=1)
loss   = (loss_i + loss_t)/2
```

Figure 3. Numpy-like pseudocode for the core of an implementation of CLIP.


(1) Contrastive pre-training
Pepper the aussie pup
Text Encoder
Image Encoder
T_1 T_2 T_3 ... T_N
I_1 I_2 I_3 ⋮ I_N
$I_1 \cdot T_1$ $I_1 \cdot T_2$ $I_1 \cdot T_3$ ... $I_1 \cdot T_N$
$I_2 \cdot T_1$ $I_2 \cdot T_2$ $I_2 \cdot T_3$ ... $I_2 \cdot T_N$
$I_3 \cdot T_1$ $I_3 \cdot T_2$ $I_3 \cdot T_3$ ... $I_3 \cdot T_N$
⋮ ⋮ ⋮ ⋱ ⋮
$I_N \cdot T_1$ $I_N \cdot T_2$ $I_N \cdot T_3$ ... $I_N \cdot T_N$

Zero-Shot Image Classification

- Given a number of classes {«dog», «cat», … }
- Create prompts: «this is an image of {class}»
- For each image, find the closest prompt
  - You can encode the text prompt and use its embedding to get a linear classification head

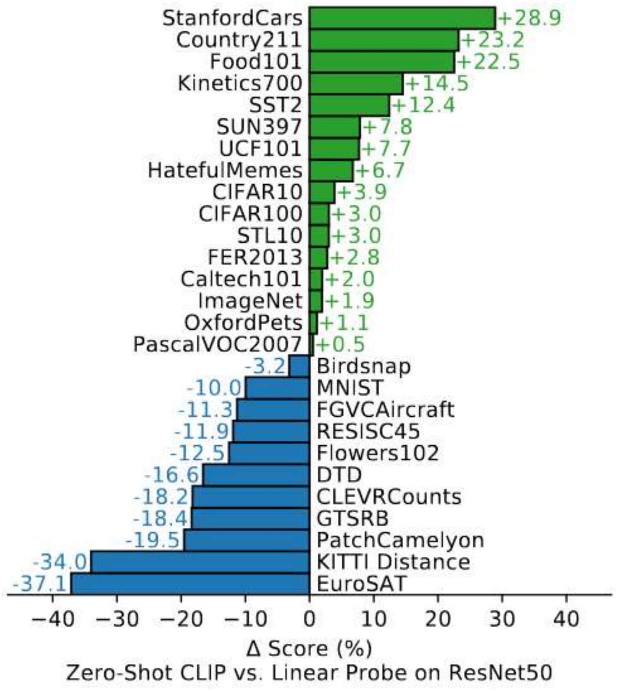


Figure 5. **Zero-shot CLIP is competitive with a fully supervised baseline.** Across a 27 dataset eval suite, a zero-shot CLIP classifier outperforms a fully supervised linear classifier fitted on ResNet-50 features on 16 datasets, including ImageNet.

Zero-Shot Image Classification

- **Ensembling**: You can use multiple prompts for the same class:
  - «a photo of a small {class}»
  - «a photo of a big {class}»
- **Prompt Engineering**: different prompts can have different results
  - E.g. «{class}» vs «a photo of {class}»
- **Paper Results**: (on ImageNet)
  - ensemble 80 different context prompts (+3.5%) w.r.t. single default prompt
  - prompt engineering and ensembling improve (+5%)
  - In general, ensembling and prompt engineering have a big impact

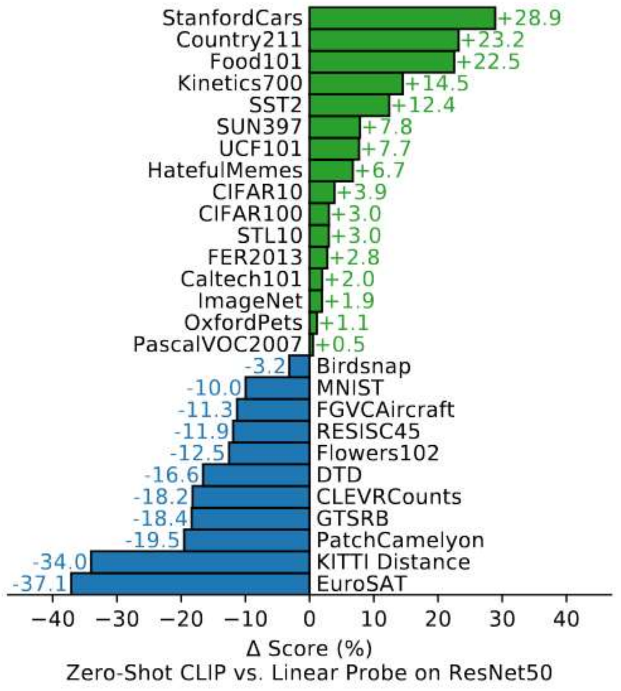


Figure 5. **Zero-shot CLIP is competitive with a fully supervised baseline.** Across a 27 dataset eval suite, a zero-shot CLIP classifier outperforms a fully supervised linear classifier fitted on ResNet-50 features on 16 datasets, including ImageNet.

CLIP Pretraining is More Sample-Efficient

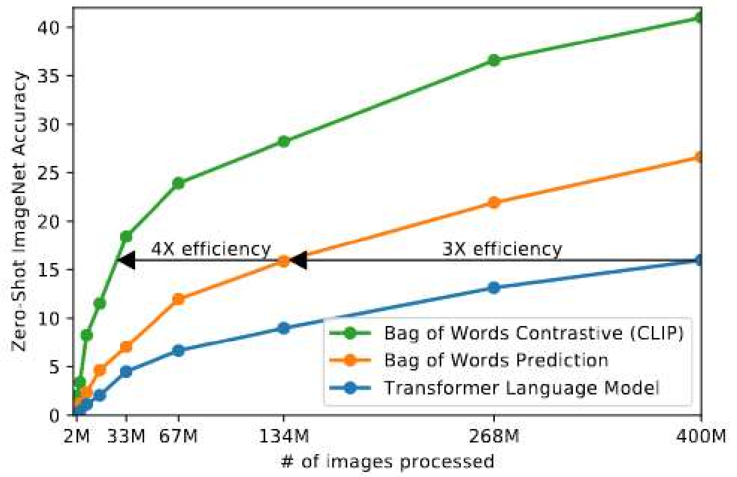
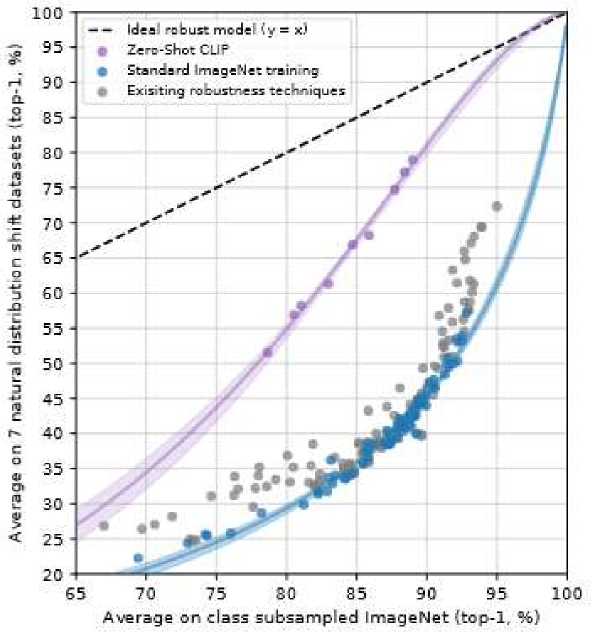


Figure 2. **CLIP is much more efficient at zero-shot transfer than our image caption baseline.** Although highly expressive, we found that transformer-based language models are relatively weak at zero-shot ImageNet classification. Here, we see that it learns 3x slower than a baseline which predicts a bag-of-words (BoW) encoding of the text (Joulin et al., 2016). Swapping the prediction objective for the contrastive objective of CLIP further improves efficiency another 4x.

A. Radford et al. 2021. "Learning Transferable Visual Models From Natural Language Supervision."

Robustness to Dataset Shift



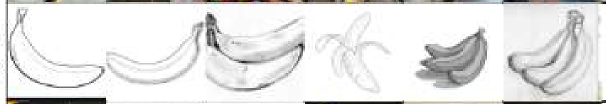
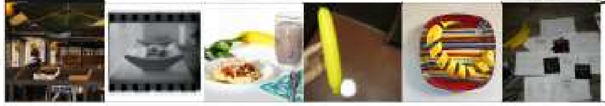
	Dataset Examples	ImageNet ResNet101	Zero-Shot CLIP	Δ Score
ImageNet		76.2	76.2	0%
ImageNetV2		64.3	70.1	+5.8%
ImageNet-R		37.7	88.9	+51.2%
ObjectNet		32.6	72.3	+39.7%
ImageNet Sketch		25.2	60.2	+35.0%
ImageNet-A		2.7	77.1	+74.4%

Figure 13. **Zero-shot CLIP is much more robust to distribution shift than standard ImageNet models.** (Left) An ideal robust model (dashed line) performs equally well on the ImageNet distribution and on other natural image distributions. Zero-shot CLIP models shrink this "robustness gap" by up to 75%. Linear fits on logit transformed values are shown with bootstrap estimated 95% confidence intervals. (Right) Visualizing distribution shift for bananas, a class shared across 5 of the 7 natural distribution shift datasets. The performance of the best zero-shot CLIP model, ViT-L/14@336px, is compared with a model that has the same performance on the ImageNet validation set, ResNet-101.

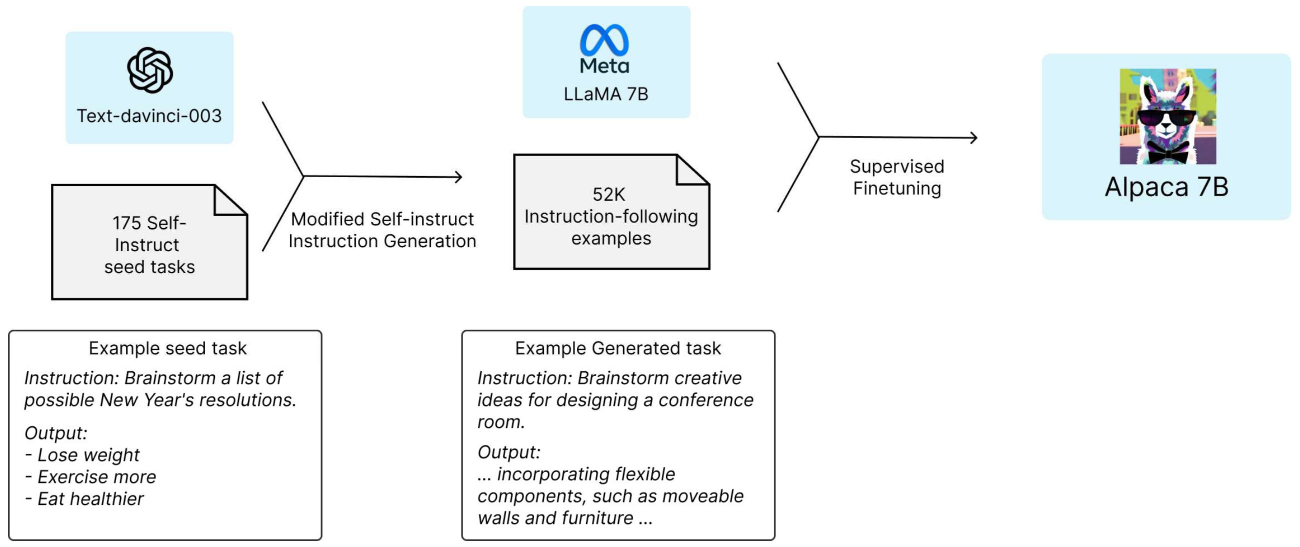
Efficient Finetuning

Distillation - Alpaca

We can use large models to create data to train the smaller models

- 7B model trained from GPT3.5 inputs
- Cheap to train
  - 3 hours on 8 80GB A100s
  - *<600$* cloud cost

- Start from LLaMA (7B LLM)
- Finetune with
  - 175 human-written instruction-output pairs
  - 52K additional pairs generated by GPT 3.5 using the human-written samples as context


Text-davinci-003
175 Self-Instruct seed tasks
Modified Self-instruct Instruction Generation
Meta
LLaMA 7B
52K Instruction-following examples
Supervised Finetuning
Alpaca 7B

Example seed task

Instruction: Brainstorm a list of possible New Year's resolutions.

Output:
- Lose weight
- Exercise more
- Eat healthier

Example Generated task

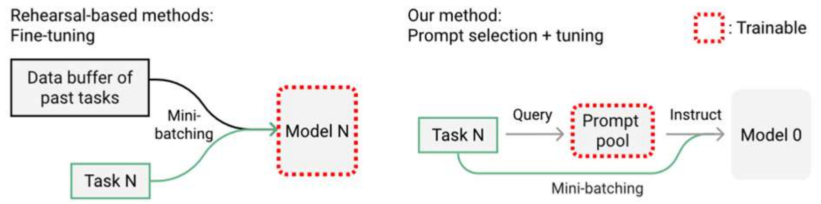
Instruction: Brainstorm creative ideas for designing a conference room.

Output:
... incorporating flexible components, such as moveable walls and furniture ...

https://github.com/tatsu-lab/stanford_alpaca

Prompt Tuning – Learning To Prompt (L2P)

- For classification problems, the prompts are fixed embedding vectors that we compare to the image embedding
- Can we learn the prompt?
- **Learning2Prompt**:
  - Continual learning method
  - Fixed pretrained backbone
  - Keep a prompt pool with <key, value> pairs
  - Uses the key to select the prompt



Rehearsal-based methods: Fine-tuning
Data buffer of past tasks
Mini-batching
Model N
Task N
Our method: Prompt selection + tuning
: Trainable
Task N
Query
Prompt pool
Instruct
Model 0
Mini-batching

Figure 1. Overview of the L2P framework. Compared with typical methods that adapt entire or partial model weights to tasks sequentially with a rehearsal buffer to avoid forgetting, L2P uses a single backbone model and learns a prompt pool to instruct the model conditionally. Task-specific knowledge is stored inside a prompt pool, thus a rehearsal buffer is no longer mandatory to mitigate forgetting. L2P automatically selects and updates prompts from the pool in an instance-wise fashion, thus task identity is not required at test time. Notably, our largest prompt space is smaller than the size of one 224×224 image.

L2P – Prompt Selection

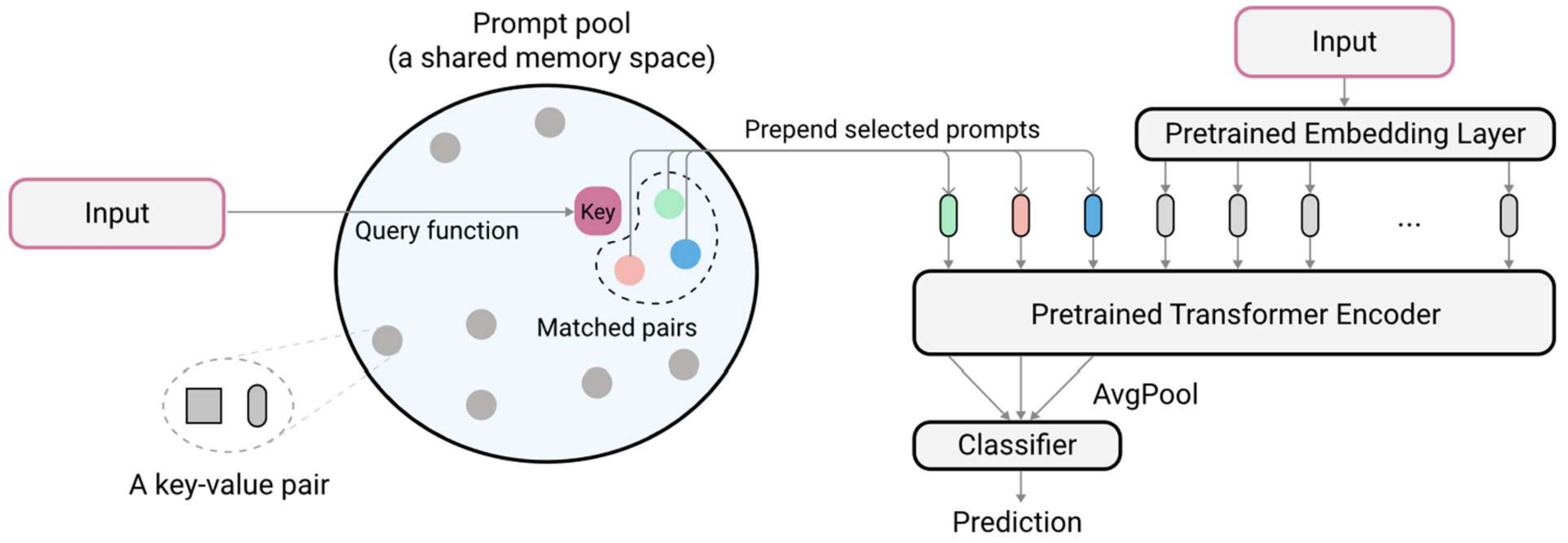


Figure 2. Illustration of L2P at test time. We follow the same procedure at training time: First, L2P selects a subset of prompts from a key-value paired *prompt pool* based on our proposed instance-wise query mechanism. Then, L2P prepends the selected prompts to the input tokens. Finally, L2P feeds the extended tokens to the model, and optimize the prompt pool through the loss defined in equation 5. The objective is learning to select and update prompts to instruct the prediction of the pre-trained backbone model.

L2P – Prompt Selection

- $\mathbf{K}_{\boldsymbol{x}} = \underset{\{s_i\}_{i=1}^{N} \subseteq [1,M]}{\operatorname{argmin}} \sum_{i=1}^{N} \gamma\left(q(\boldsymbol{x}), \boldsymbol{k}_{s_i}\right)$ **Prompt Selection**
  - $q(\boldsymbol{x})$ pretrained feature extractor gets query features
  - $\boldsymbol{k}_{s_i}$ key
  - γ scoring function that matches image and prompts

- $\underset{\mathbf{P},\mathbf{K},\phi}{min} \mathcal{L}\left(g_\phi\left(f_r^{\text{avg}}\left(\boldsymbol{x}_p\right)\right), y\right) + \lambda \sum_{\mathbf{K}_{\boldsymbol{x}}} \gamma\left(q(\boldsymbol{x}), \boldsymbol{k}_{s_i}\right)$ **Optimization Objective**
  - f_r^{avg} ViT encoder
  - g_ϕ classifier

Efficient Finetuning – Low Rank Adaptation (LoRA)

- We can finetune only a small part of the model
- Represent the finetuned models as $\Phi_0 + \Delta\Phi$ with small (in memory size) $\Delta\Phi$
  - This allows us to easily train and store hundreds of finetuned models
- Low-Rank Parameter Update
  - $h = W_0 x + \Delta W x = W_0 x + BAx$
  - With $B \in \mathbb{R}^{d \times r}, A \in \mathbb{R}^{r \times k}, r \ll d$

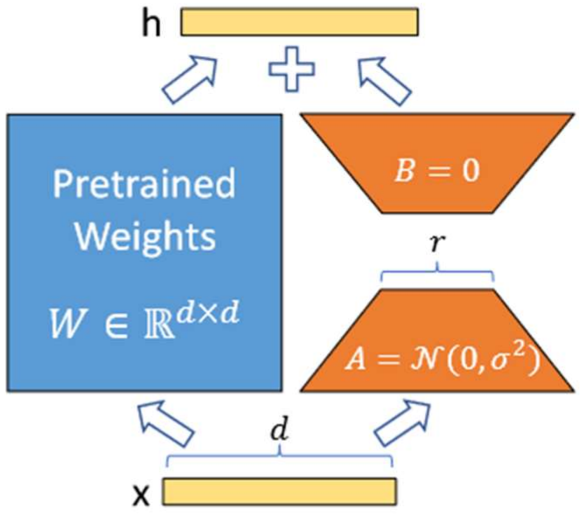
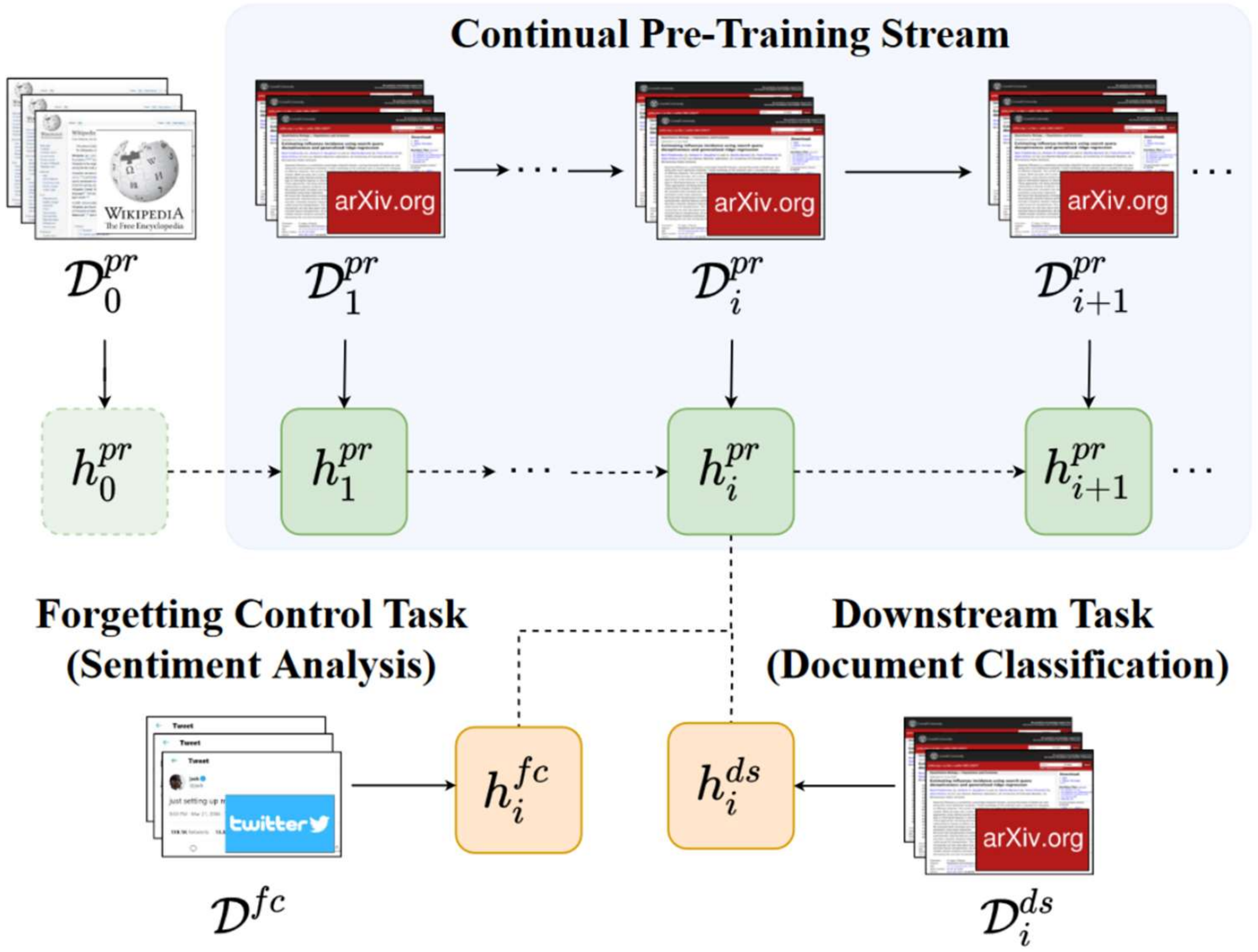

h
Pretrained Weights
$W \in \mathbb{R}^{d \times d}$
$B = 0$
r
$A = \mathcal{N}(0, \sigma^2)$
d
x

Figure 1: Our reparametrization. We only train A and B.

Continual Pretraining

Continual Pretraining

- **Continual Pretraining** is the problem of efficiently updating a large pretrained model
- **Forgetting Control Task**: we don’t want to forget general knowledge
- **Downstream Task**: we want to improve on domain-specific tasks



Pretraining Results

Evaluation on the Forgetting Control Task

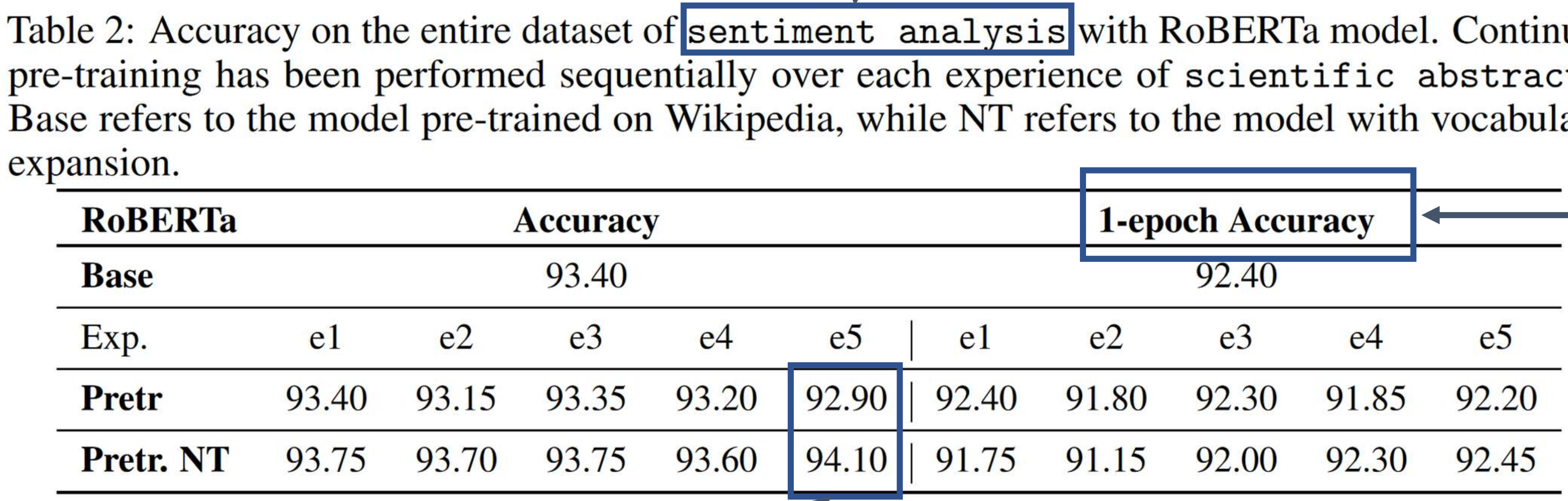


Table 2: Accuracy on the entire dataset of `sentiment analysis` with RoBERTa model. Continual pre-training has been performed sequentially over each experience of `scientific abstracts`. Base refers to the model pre-trained on Wikipedia, while NT refers to the model with vocabulary expansion.

RoBERTa	**Accuracy**					**1-epoch Accuracy**				
Base	93.40					92.40				
Exp.	e1	e2	e3	e4	e5	e1	e2	e3	e4	e5
Pretr	93.40	93.15	93.35	93.20	92.90	92.40	91.80	92.30	91.85	92.20
Pretr. NT	93.75	93.70	93.75	93.60	94.10	91.75	91.15	92.00	92.30	92.45

fast adaptation

Forgetting is limited even with finetuning. Dynamic vocabulary expansion (NT) slightly improves the performance.

Self-supervised pretraining is more robust than supervised methods (result for vision in the paper)

Self-Supervised CL

- Distillation loss maps old representations in a new projected space
- SSL tricks such as heavy augmentations and SSL losses
- Linear probing evaluation

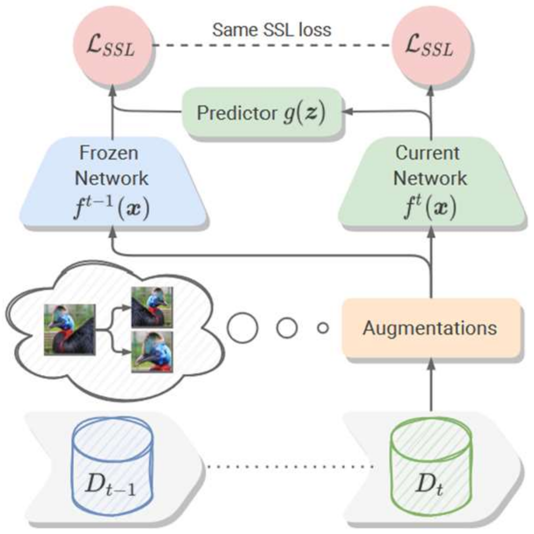


Figure 2. Overview of the CaSSLe framework.

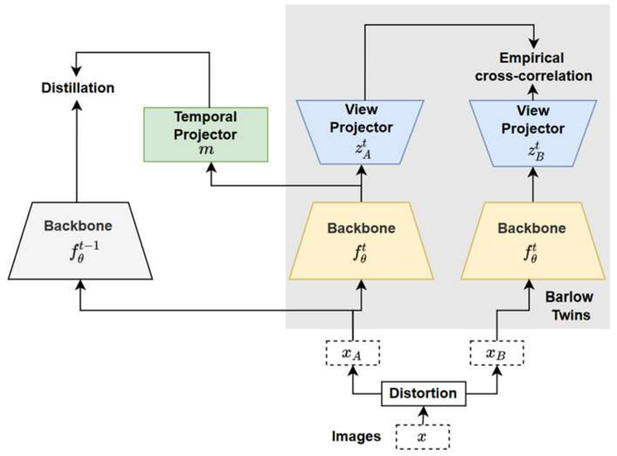


Figure 1. Self-supervised continual learning with Projected Functional Regularization. Instead of performing feature distillation directly between the previous task backbone and the new one, we use a *learned temporal projection* between the two feature spaces.

A. Gomez-Villa et al. "Continually Learning Self-Supervised Representations With Projected Functional Regularization," CLVISION '22
E. Fini et al. "Self-Supervised Models Are Continual Learners." CVPR '22

CaSSLe – Self-Supervised CL

- We can also use KD to train SSL models
- SSL loss on new data + KD loss on old embeddings

$$\mathcal{L} = \mathcal{L}_{SSL}(\boldsymbol{z}^A, \boldsymbol{z}^B) + \mathcal{L}_D\left(\boldsymbol{z}^A, \bar{\boldsymbol{z}}^A\right)$$
$$= \mathcal{L}_{SSL}(\boldsymbol{z}^A, \boldsymbol{z}^B) + \mathcal{L}_{SSL}\left(g(\boldsymbol{z}^A), \bar{\boldsymbol{z}}^A\right).$$

- A and B images, z^A, z^B embeddings of new model
- $\bar{\boldsymbol{z}}^A$ embedding of old model
- $\mathcal{L}_{SSL}$ is used as the distillation loss
- g is a projection network that maps from the new representation to the old ones
  - Allows to update the representations and change them

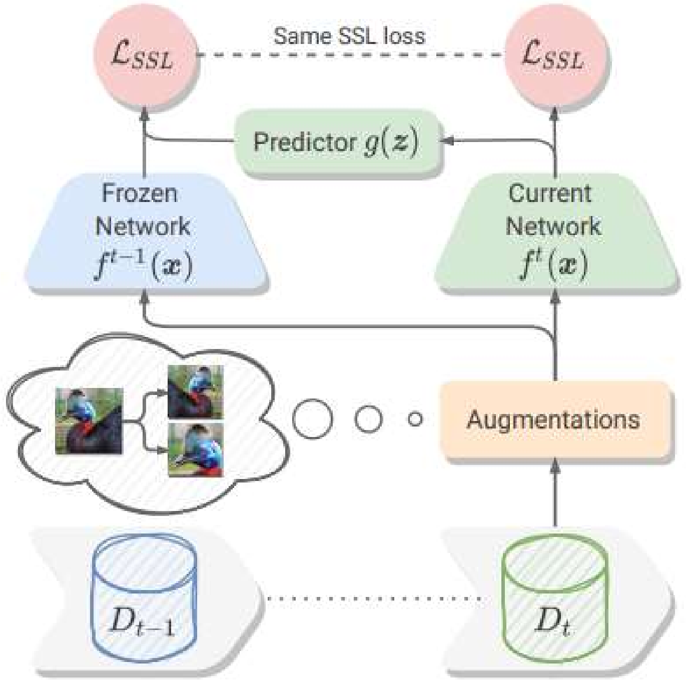


Figure 2. Overview of the CaSSLe framework.

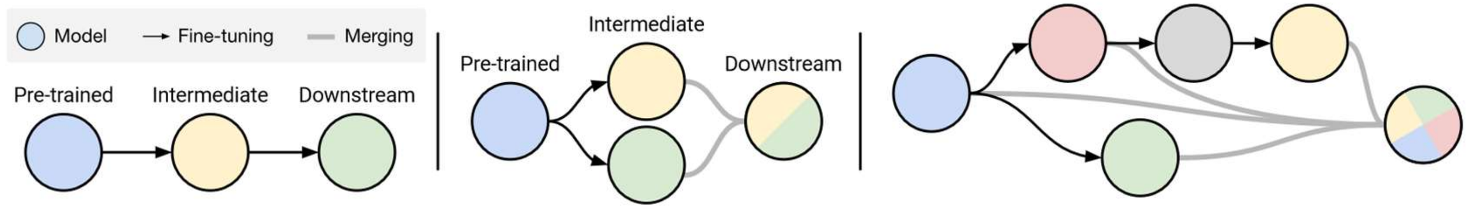
Large-Scale Pretraining

- self-supervised pretraining provides very general knowledge about large domains (vision, language)
  - We can adapt them to solve new tasks with few (or zero) examples
  - They are more robust compared to supervised models
  - They are even more robust than finetuned models

Model Patching

Building Models like OSS

Community-developed and continually-improved models
- Incremental and cheaply-communicable updates
- Merging models
- vetting community contributions
- versioning and backward compatibility
- Modularity and distribution



https://colinraffel.com/blog/a-call-to-build-models-like-we-build-open-source-software.html

Model Patching

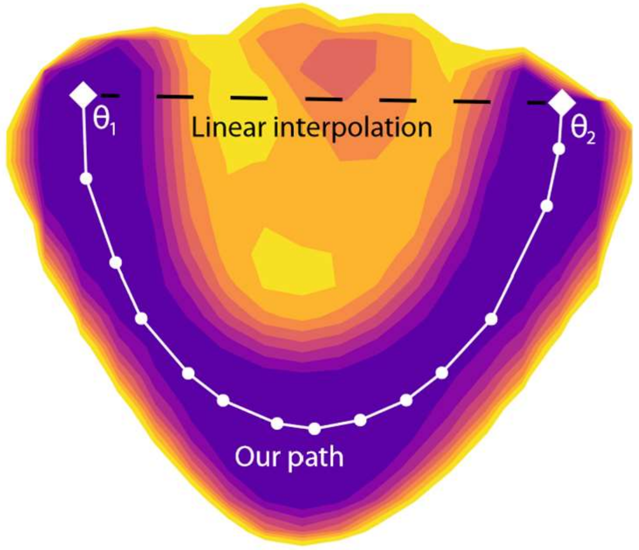
GOAL: we want to consolidate two pretrained models

- Given two models f_{θ_1} and f_{θ_2} trained on tasks T1 and T2
- Find a model f_{θ_M} that solves both T1 and T2
- The two models can have different architectures, initialization, training algorithm, tasks…

(nonlinear) Mode Connectivity

Mode Connectivity: the models (modes) are connected by a low-loss path.

- we construct continuous paths between minima of recent neural network architectures on CIFAR10 and CIFAR100."
- "we observe the following trend: The deeper and wider an architecture, the lower are the saddles between minima until they essentially vanish for current-day deep architectures.
- The more complex dataset CIFAR100 raises the barriers."
- AutoNEB: method for connecting minima from molecular statistical mechanics



F. Draxler et al. "Essentially No Barriers in Neural Network Energy Landscape,"

Simple Model Patching

Linear Mode Connectivity:

- Naive average: $\theta^{M} = \frac{1}{2}\left(\theta^{1} + \theta^{2}\right)$
- Weighted average: $\theta_i^{M} = \alpha_i \theta_i^{1} + (1 - \alpha_i)\theta_i^{2}$

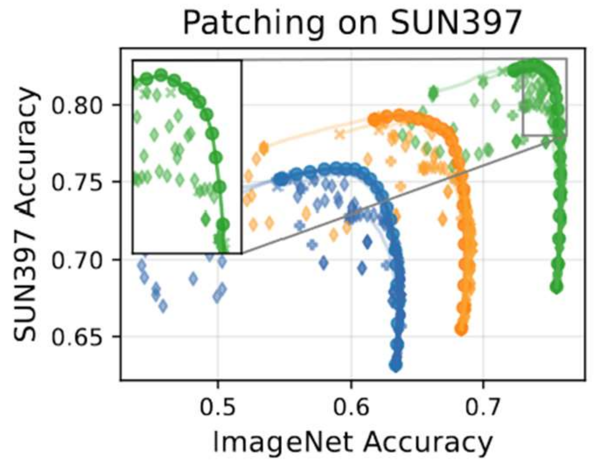
How do we find the weights?

- (normalized) Fisher diagonal
- (normalized) gradients
- Optimizing on a validation set

Patching Vision-Language Models

- open-vocabulary models are characterized by their ability to perform any image classification task (example: CLIP)
- based on text descriptions of the classes

PAINT also allows a single model to be patched on multiple tasks and improves with model scale. Furthermore, we identify cases of broad transfer, where patching on one task increases accuracy on other tasks



Step 1. Fine-tune θ_{zs} on training data from $\mathcal{D}_{patch}$ to produce a model with weights θ_{ft}.
Step 2. For mixing coefficient $\alpha \in [0, 1]$, linearly interpolate between θ_{zs} and θ_{ft} to produce $\theta_{patch} = (1 - \alpha) \cdot \theta_{zs} + \alpha \cdot \theta_{ft}$. The mixing coefficient is determined via held-out validation sets for $\mathcal{D}_{supp}$ and $\mathcal{D}_{patch}$. We refer to the resulting model as θ_{patch}.

G. Ilharco et al. «Patching open-vocabulary models by interpolating weights" NeurIPS 2022

Git-Rebasin

- IDEA: we can exploit DNN symmetries to find a «better alignment» between the models that allows to patch them via weight averaging (remember: no barriers in loss)

- DNN units can be permuted without changin the DNN output:

$$\boldsymbol{W}'_\ell = \boldsymbol{P}_\ell \boldsymbol{W}_\ell^{(B)} \boldsymbol{P}_{\ell-1}^\top, \quad \boldsymbol{b}'_\ell = \boldsymbol{P}_\ell \boldsymbol{b}_\ell^{(B)}$$

- Git-Rebasin: find the best unit permutations by matching weights or activations. Then, we can merge with the naïve average.

Ainsworth, S. K., et al. "Git Re-Basin: Merging Models modulo Permutation Symmetries".

What are we missing?

Necessary conditions for mode connectivity are unclear

- **initialization?**
  - Pretrained models are the best choice -> if the first part of the training is shared patching becomes much easier.
  - Same init is better. Different init works for simple datasets?
- **Width and depth?** Wider is better, but is it always enough? How wide should it be? How quickly is it growing with dataset complexity?
- **Optimizer?** Adaptive vs non-adaptive
- **Architecture?** Transformers, residual connections, batchnorm…

Are Transformers Meta-Learning Methods?

In-Context Learning

- What is in-context learning (ICL) and why does it work so well?
- Is ICL even learning?
- Is it just an emergent property of large pretraining/data/architecture?

- **IDEA**: If ICL is a learning algorithm, then pretraining is a «meta-learning» algorithm

Motivation – Learning to Learn

- **Meta-learning**: Can we optimize the learning algorithm to solve novel tasks (transfer, low-shot and fast adaptation, hyperparameter search)? *a.k.a. Learning to learn*
  - $\mathcal{A}^{META}: \{\mathcal{D}_1, \dots, \mathcal{D}_N\} \rightarrow \mathcal{A}^*, \mathcal{A}^*: \mathcal{D}_{N+1}^{\text{train}} \rightarrow \theta^{N+1}$

- **Example: Optimization-based meta learning (MAML)**
  - $\theta^* = \min_{\theta} \mathbb{E}_{p(\mathcal{T})} \left[\mathcal{L}_{\mathcal{T}} \left(U_k \left(\theta, D_{\tau}^{Supp} \right), D_{\tau}^{query} \right) \right]$
  - Learn the best init

Hypothesis: ICL is a form of SGD

- “we suggest that training Transformers on auto-regressive objectives is closely related to gradient-based metalearning formulations”
- “trained Transformers become mesa-optimizers i.e. learn models by gradient descent in their forward pass.”
- The paper provides a constructive proof of this behavior for regression problems
  - Note that this means that maybe ICL is not a consequence of large-scale training, but of the Transformer architecture

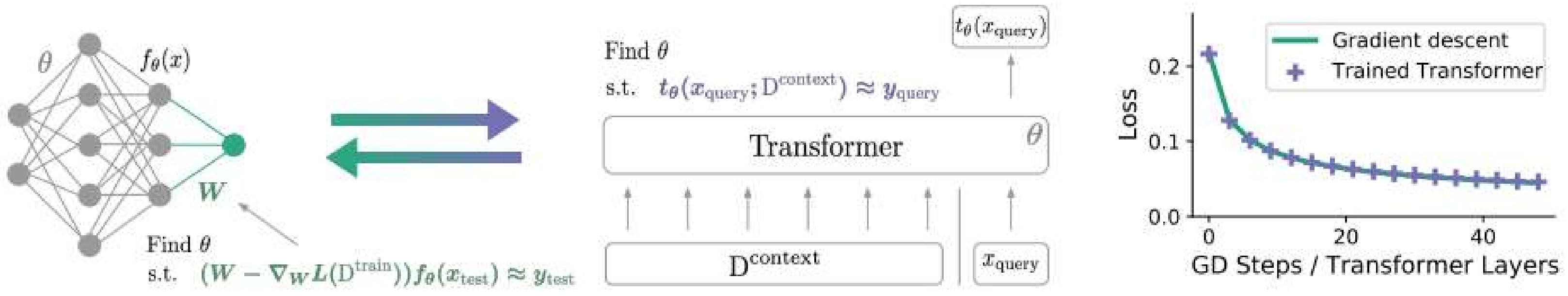
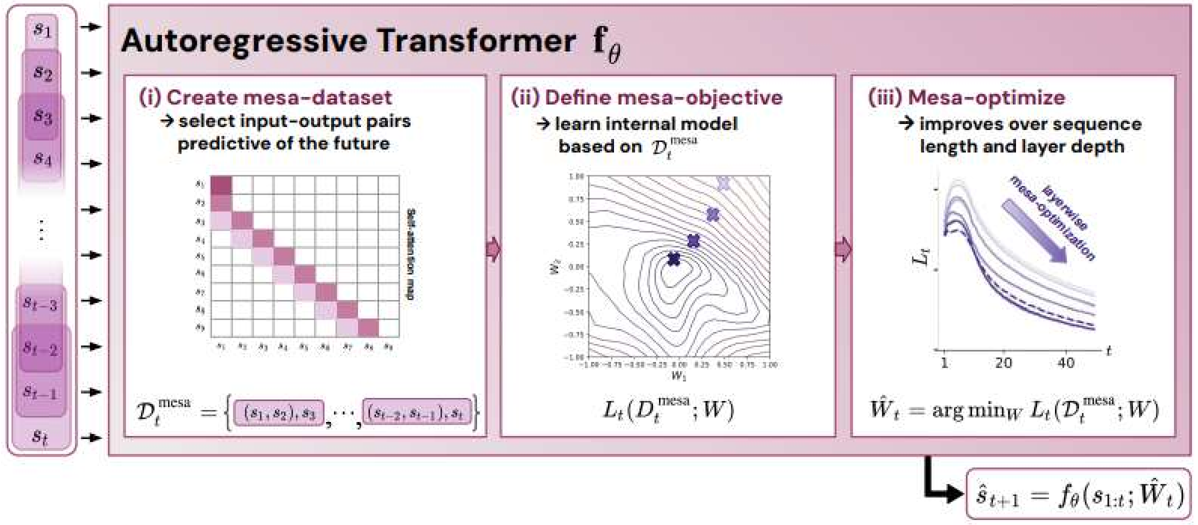

θ
$f_\theta(x)$
W
Find θ
s.t. $(W - \nabla_W L(D^{\text{train}}))f_\theta(x_{\text{test}}) \approx y_{\text{test}}$
Find θ
s.t. $t_\theta(x_{\text{query}}; D^{\text{context}}) \approx y_{\text{query}}$
$t_\theta(x_{\text{query}})$
Transformer
θ
D^{context}
x_{query}
Gradient descent
Trained Transformer
Loss
0.2
0.1
0.0
0
20
40
GD Steps / Transformer Layers

Figure 1. **Illustration of our hypothesis: gradient-based optimization and attention-based in-context learning are equivalent.** *Left*: Learning a neural network output layer by gradient descent on a dataset D^{train}. The task-shared meta-parameters θ are obtained by meta-learning with the goal that after adjusting the neural network output layer, the model generalizes well on unseen data. *Center*: Illustration of a Transformer that adjusts its query prediction on the data given in-context i.e. $t_\theta(x_{\text{query}}; D^{\text{context}})$. The weights of the Transformer are optimized to predict the next token y_{query}. *Right*: Our results confirm the hypothesis that learning with K steps of gradient descent on a dataset D^{train} (*green part of the left plot*) matches trained Transformers with K linear self-attention layers (*central plot*) when given D^{train} as in-context data D^{context}.

Von Oswald, Johannes, et al. "Transformers learn in-context by gradient descent." *International Conference on Machine Learning*. PMLR, 2023. 59

Hypothesis: ICL is a form of SGD

- “We reverse-engineer Transformers trained on simple sequence modeling tasks, and find strong evidence that their forward pass implements two-step algorithms: (i) early self-attention layers construct internal training datasets by grouping and copying tokens, and therefore implicitly define internal objective functions, (ii) deeper layers optimize these objectives to generate predictions.”



Autoregressive Transformer f_θ
(i) Create mesa-dataset
→ select input-output pairs predictive of the future
self-attention map
$\mathcal{D}_t^{\text{mesa}} = \{(s_1, s_2), s_3, \cdots, (s_{t-2}, s_{t-1}), s_t\}$
(ii) Define mesa-objective
→ learn internal model based on $\mathcal{D}_t^{\text{mesa}}$
$L_t(D_t^{\text{mesa}}; W)$
(iii) Mesa-optimize
→ improves over sequence length and layer depth
layerwise mesa-optimization
L_t
$\hat{W}_t = \arg\min_W L_t(\mathcal{D}_t^{\text{mesa}}; W)$
$\hat{s}_{t+1} = f_\theta(s_{1:t}; \hat{W}_t)$

Figure 1: **Illustration of our hypothesis:** Optimizing the weights θ of an autoregressive Transformer f_θ gives rise to mesa-optimization algorithms implemented in the forward pass of the model. As a sequence of inputs $s_1, \ldots, s_t$ is processed up to timestep t, the Transformer (i) creates an internal training set consisting of pairs of input-target associations, (ii) defines an internal objective function through the resulting dataset, used to measure the performance of an internal model with weights W, (iii) optimizes this objective and uses the learned model to generate a prediction $\hat{s}_{t+1}$ of the future.

Conclusion

Take-Home Messages

- scale matters
- Be careful about the evaluation
  - It’s easy to evaluate on the training set
  - companies are not sharing many details about the models (evaluation, training data, number of parameters)
- methods that we saw in the course are used (is slightly different forms)
  - distillation to reduce the size of the model
  - zero-shot and few-shot techniques (e.g. prompting)
  - finetuning (e.g. LoRA)