# Representation Learning
# Pre-training

# Example in image representation

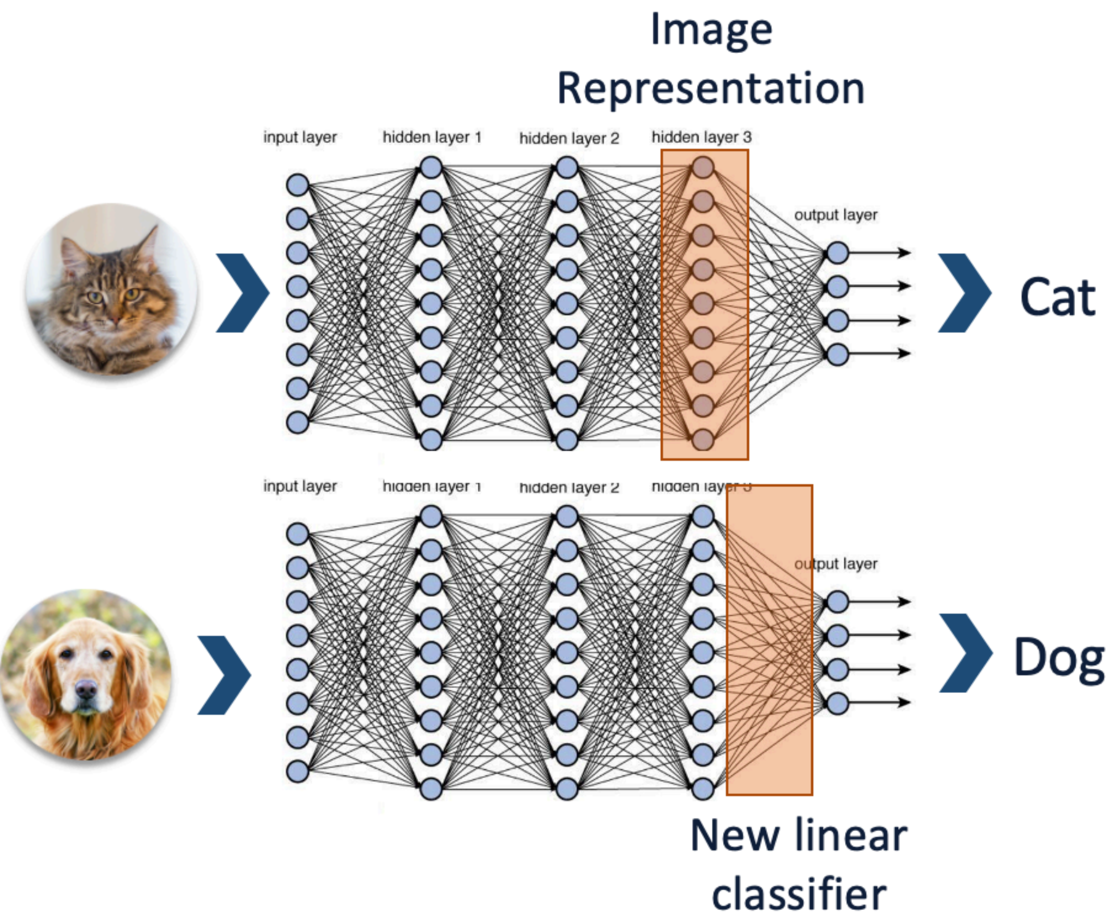


Image Representation

Cat

Dog

New linear classifier

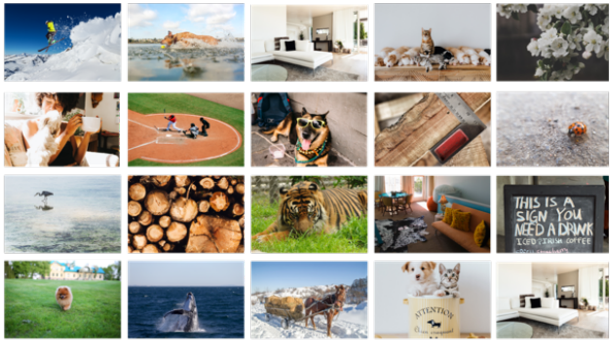
Train a neural network (ResNet) on ImageNet (1M data, 1000 classes)

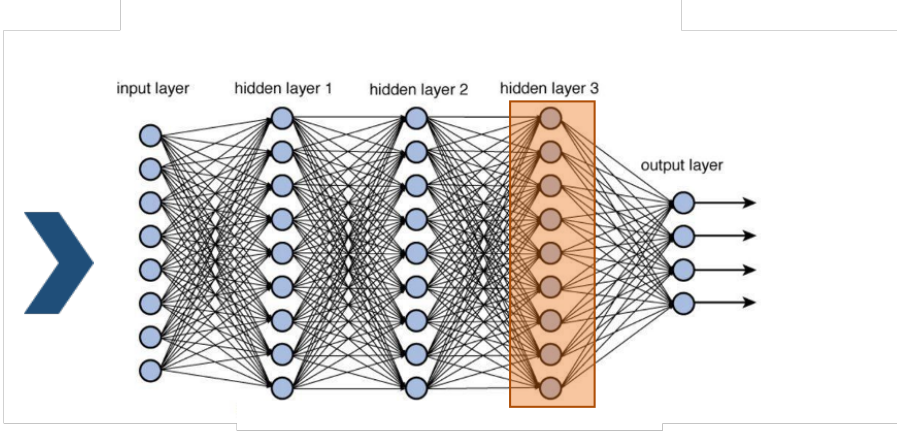
**Representation (feature extractor):** The mapping from image to the second-to-the-last layer.

Fix the representation, just re-train the last linear layer.

# Example in image representation

**Source tasks** (for training representation): ImageNet





**Target task:** Few-shot Learning on VOC07 dataset (20 classes, 1-8 examples per class)

- Without representation learning: **5% - 10%** (random guess = **5%)**
- With representation learning: **50% - 80%**

# Example in image representation

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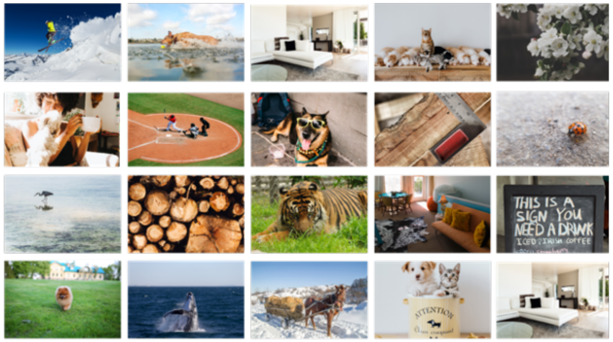

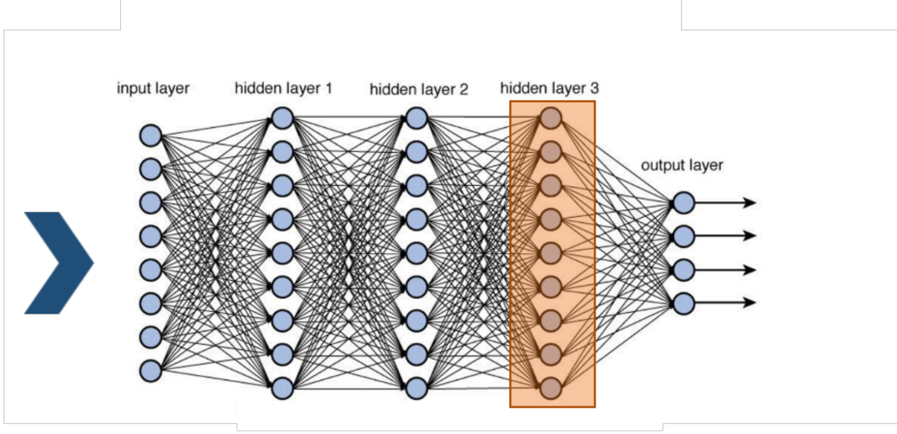

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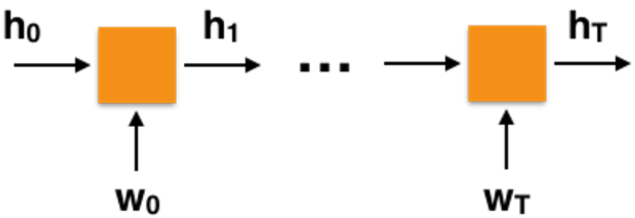
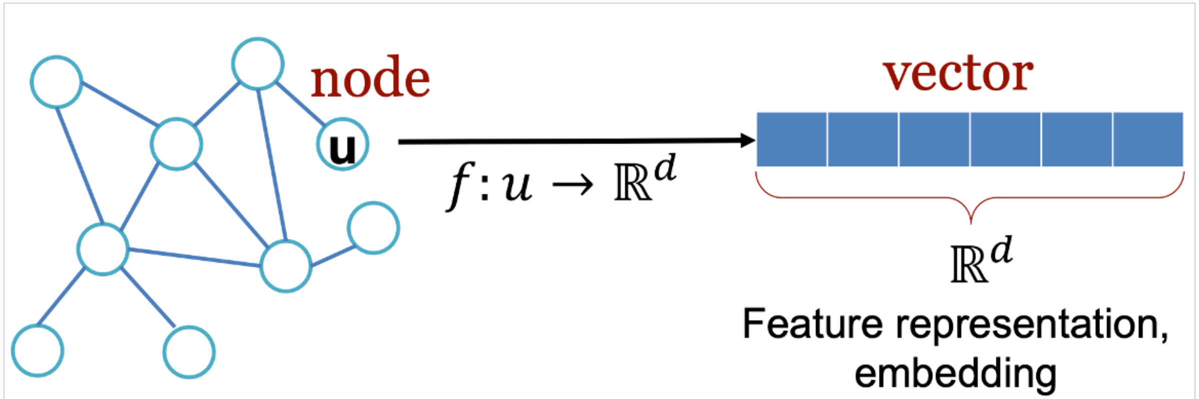
# Examples

Natural Language Processing



Final hidden state:
Sentence representation

Graph Representation Learning



Feature representation, embedding

# Representation learning

- A function that maps the raw input to a compact representation (feature vector). Learn an **embedding / feature / representation** from **labeled/unlabeled data.**
- Supervised:
    - Multi-task learning
    - Meta-learning
    - Multi-modal learning
    - …
- Unsupervised:
    - PCA
    - ICA
    - Dictionary learning
    - Sparse coding
    - Boltzmann machine
    - Autoencoder
    - Contrastive learning
    - Self-supervised learning
    - …

# Desiderata for representations

Many possible answers here.

- **Downstream usability:** the learned features are "useful" for downstream tasks:
    - Example: a linear (or simple) classifier applied on the learned features only requires a small number of labeled samples. A classifier on raw inputs requires a large mount of data.

- **Interpretability:** the learned features are semantically meaningful, interpretable by a human, can be easily evaluated.
    - Not well-defined mathematically.
    - **Sparsity** is an important subcase.

# Desiderata for representations

From Bengio, Courville, Vincent ’14:

- **Hierarchy / compositionality:** video/image/text are expected to have hierarchial structure: need *deep* learning.

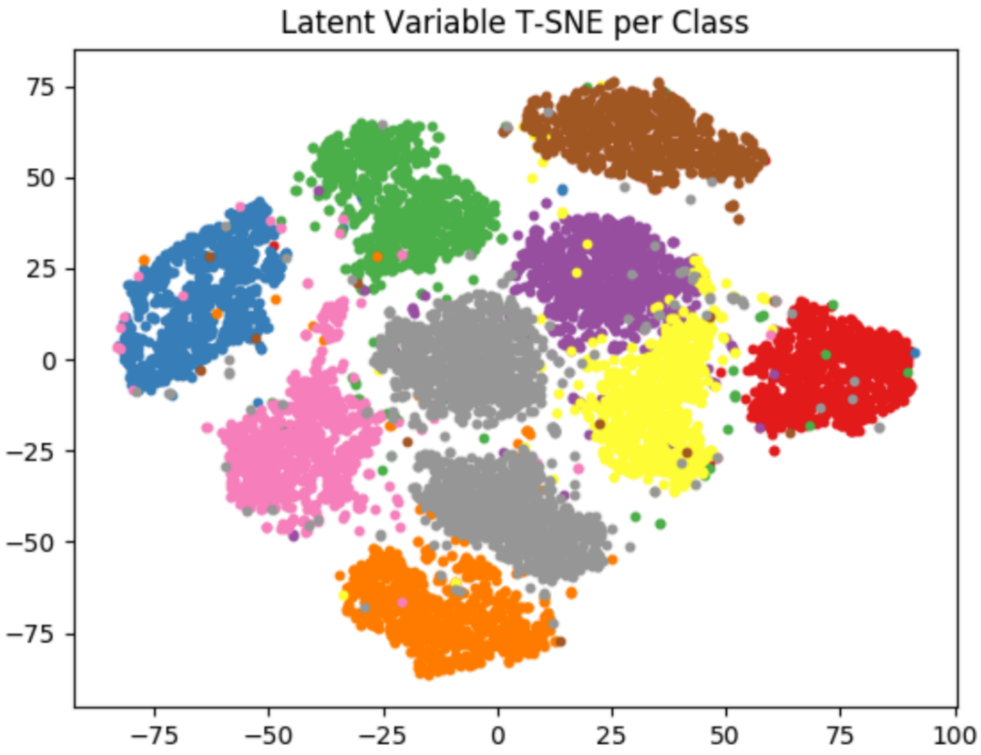
- **Semantic clusterability**: features of the same “semantic class” (e.g. images in the same class) are clustered together.

- **Linear interpolation**: in the representation space, linear interpolations produce meaningful data points (latent space is convex). Also called *manifold flattening.*

- **Disentanglement**: features capture “independent factors of variation” of data. A popular principle in modern unsupervised learning.

# Semantic clustering

**Semantic clusterability:** features of the same "semantic class" (e.g. images in the same class) are clustered together.

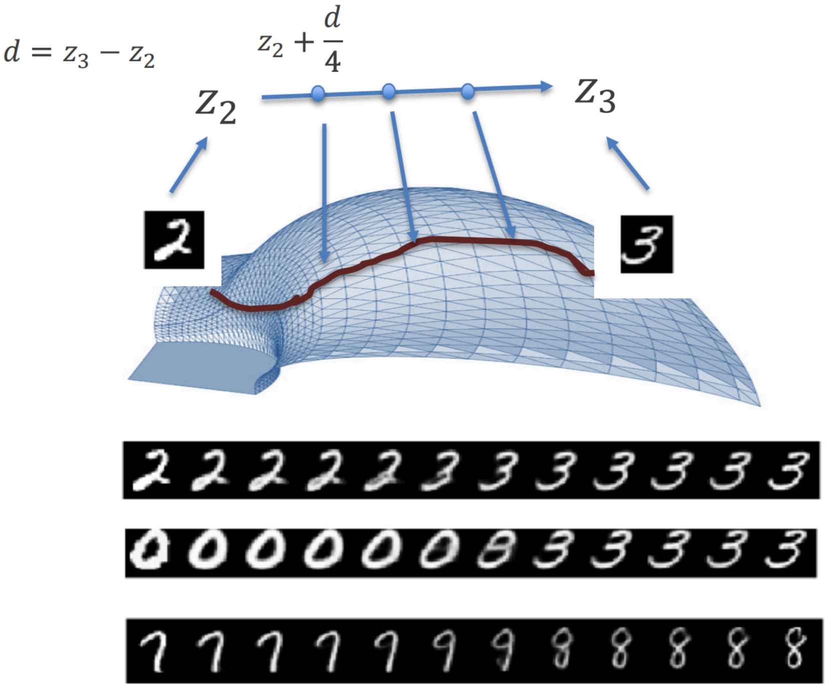


**Intuition:** If semantic classes are linearly separable, and labels on downstreams tasks depend linearly on semantic classes: we only need to learn a simple classifer.

t-SNE projection (a data visualization method) of VAE-learned features of 10 MNIST classes.

# Linear interpolation

**Linear interpolation:** in the representation space, linear interpolations produce meaningful data points (latent space is convex).



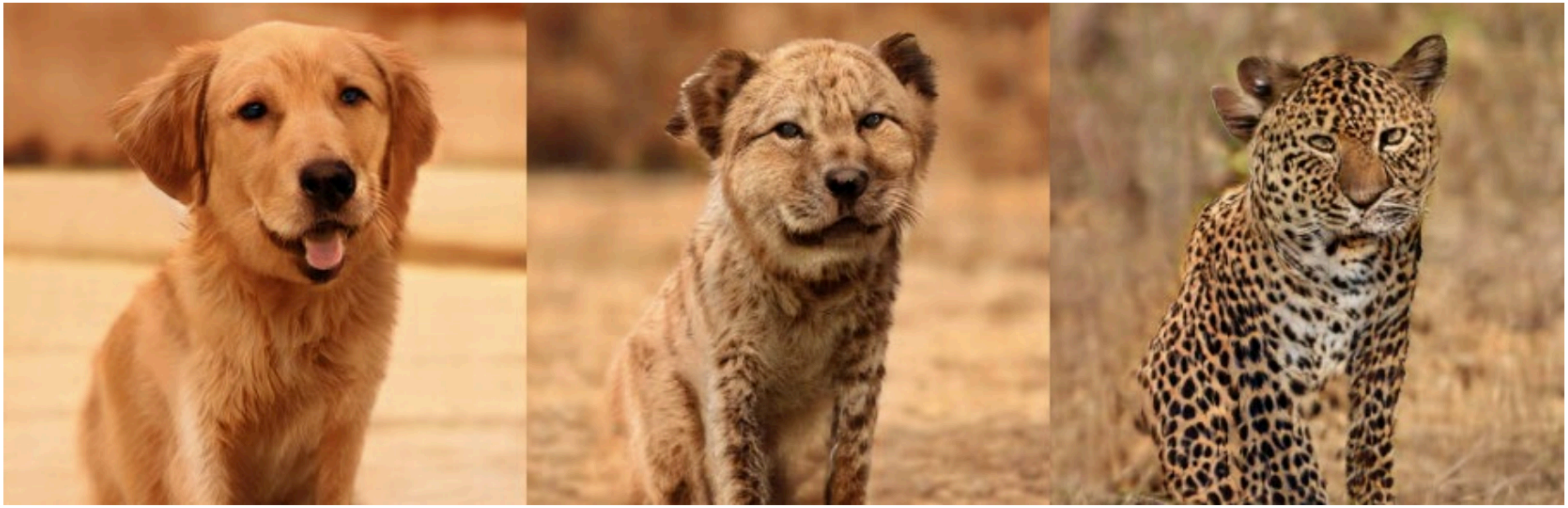
**Intuition:** the data lies on a manifold which is complicated/ curved.

The latent variable manifold is a convex set: moving in straight lies is still on it.

Interpolations for a VAE trained feature on MNIST.

# Linear interpolation

**Linear interpolation:** in the representation space, linear interpolations produce meaningful data points (latent space is convex).



Interpolations for a BigGAN image.

# Disentanglement

**Disentanglement:** features capture "independent factors of variation" of data (Bengio, Courville, Vincent '14).

- Very popular in modern unsupervised learning.
- Strong connections with generative models: $p_\theta(z) = \Pi_i p_\theta(z_i)$.

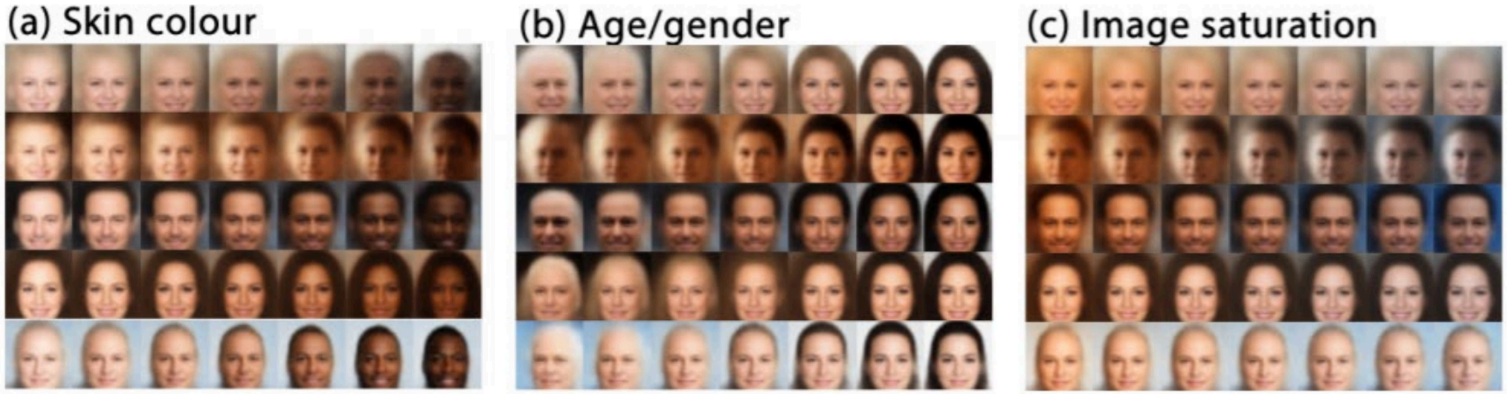


Figure 4: **Latent factors learnt by $\beta$-VAE on celebA:** traversal of individual latents demonstrates that $\beta$-VAE discovered in an unsupervised manner factors that encode skin colour, transition from an elderly male to younger female, and image saturation.

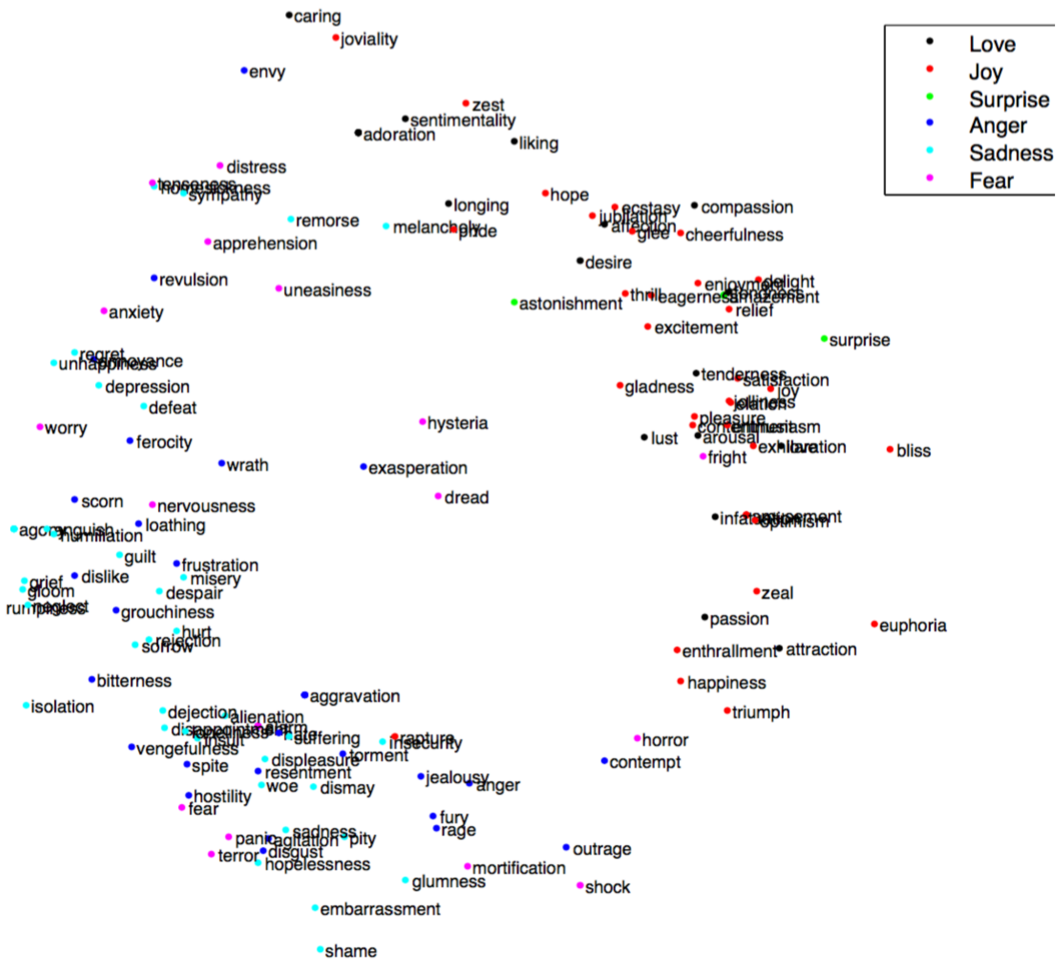
# Pre-training Learning Methods for Text

# Word embeddings, word2vec

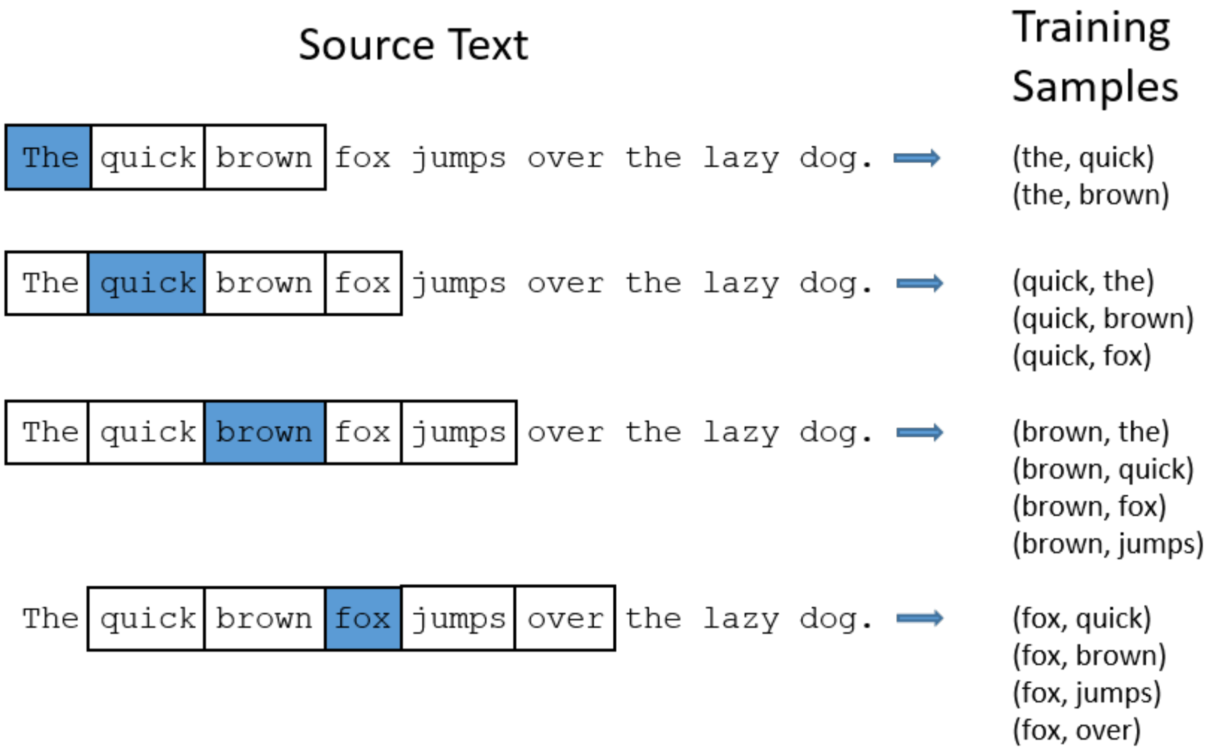
Can we **embed words** into a latent space?

This embedding came from directly querying for relationships.

**word2vec** is a popular unsupervised learning approach that just uses a text corpus (e.g. nytimes.com)



# Word embeddings, word2vec



slide: http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/

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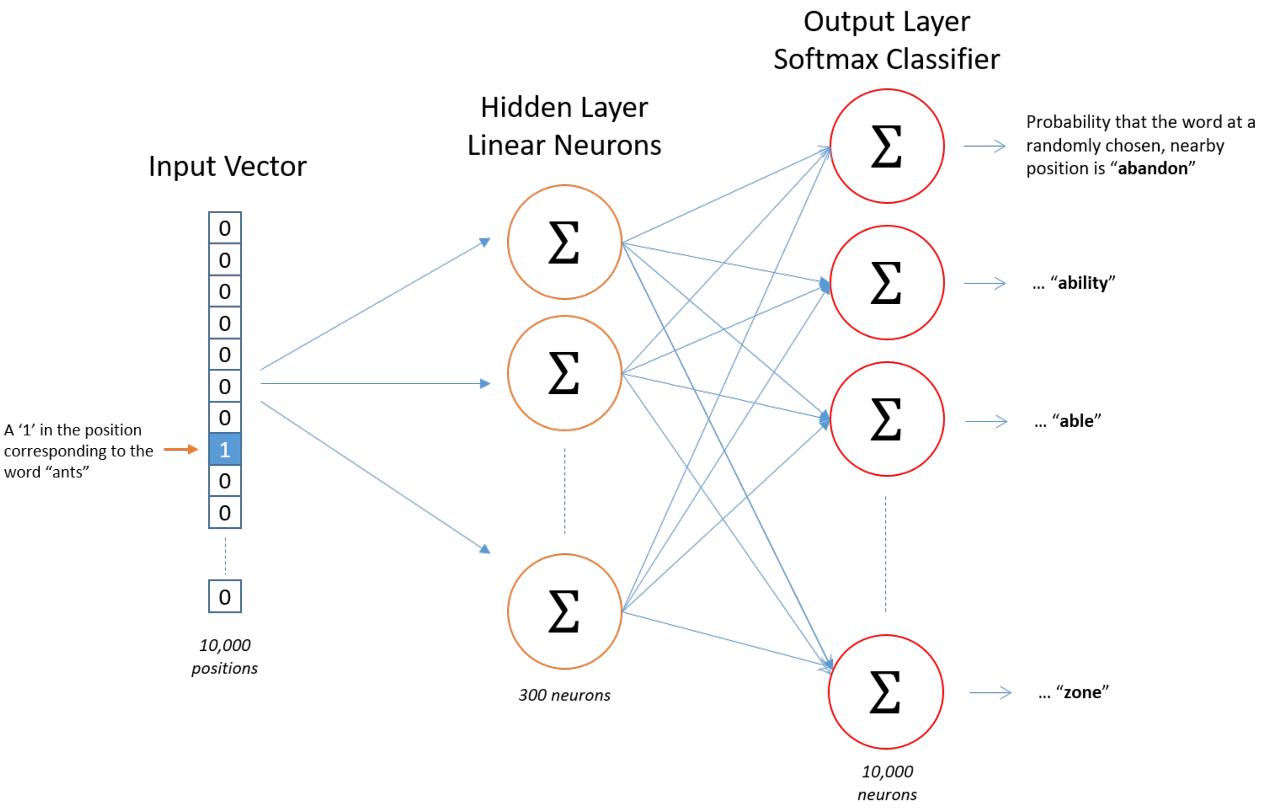
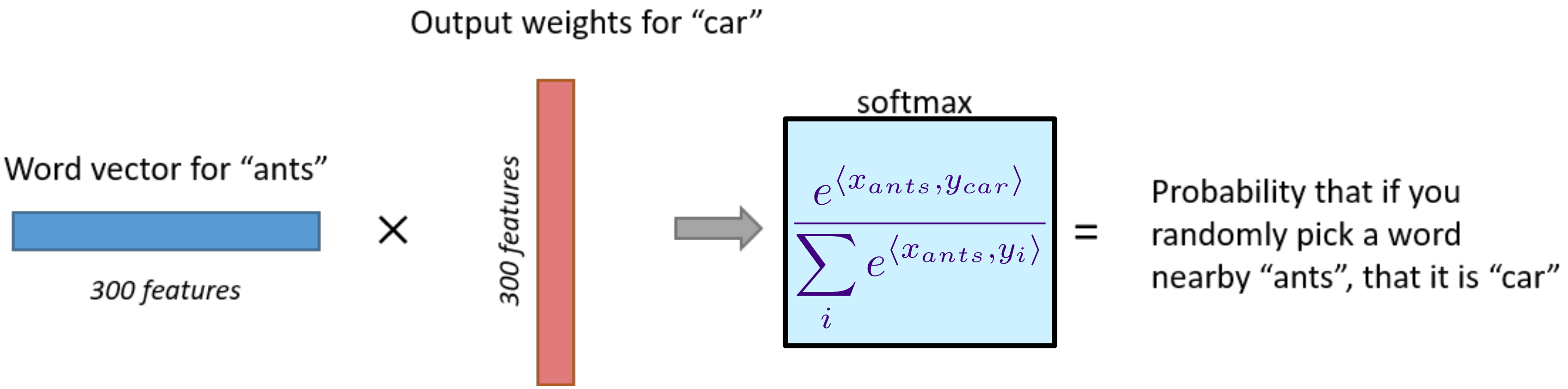


Training neural network to predict co-occuring words. Use first layer weights as embedding, throw out output layer

slide: http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/

# Word embeddings, word2vec



$$\frac{e^{\langle x_{ants}, y_{car} \rangle}}{\sum_i e^{\langle x_{ants}, y_i \rangle}} =$$

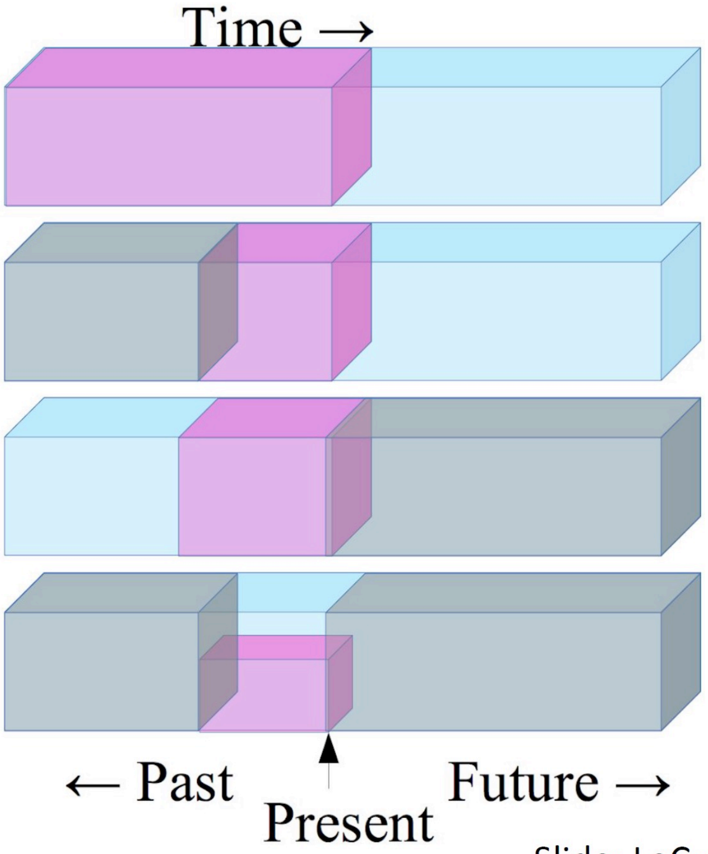
Probability that if you randomly pick a word nearby “ants”, that it is “car”

Training neural network to predict co-occuring words. Use first layer weights as embedding, throw out output layer

slide: http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/

# Self-supervised learning

- Predict any part of the input from any other part.
- Predict the future from the past.
- Predict the future from the recent past.
- Predict the past from the present.
- Predict the top from the bottom.
- Predict the occluded from the visible
- Pretend there is a part of the input you don't know and predict that.



Slide: LeCun

# Tokenizer

- Break raw text into smaller units (tokens).
    - raw text can be document, code, math, etc.
- A language model places a probability distribution over sequences of tokens.

- Raw text: string = "Hello, 🌍! 你好!”
- indices = [15496, 11, 995, 0]
- Two functions:
    - Encode: from string to indices
    - Decode: from indices to a string

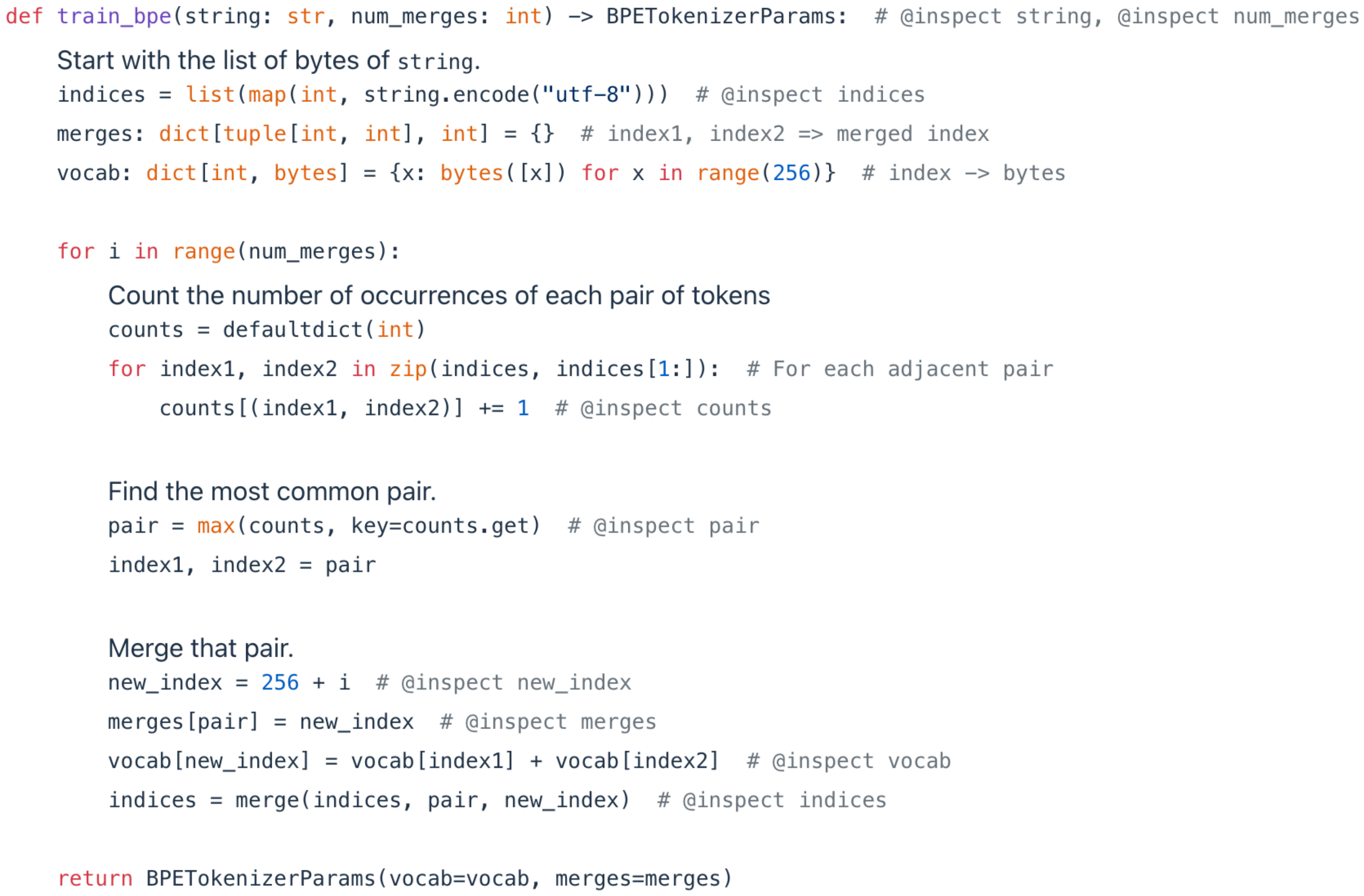
- Metric: compression ratio
    - How many original characters or bytes are represented by one token on average
    - Depends on text distribution, vocabulary size (often 32k - 50k), etc
    - English: 3-4 chars/token, Chinese/Japanese/Korean: 1-1.8 chars/token, Code: 2-3 chars/tokens, Math/Latex: 1-2 chars/token.

# Tokenizers

- Character-based tokenization: bad compression ratio
  - ord("🌍") == 127757, chr(127757) == “🌍"
- Byte-based tokenization (UTF-8): bad compression ratio
  - bytes("🌍", encoding="utf-8") == b”\xf0\x9f\x8c\x8d"
- Word-based tokenization:
  - Split strings into words, then construct encoding/decoding.
  - # of words is huge, many words are rare, no fixed voc size.

- **Byte Pair Encoding (BPE):**
  - An algorithm by Philip Gage (1994).
  - Adopted in machine translation. Used in GPT-2.
  - Idea: **train** the tokenizer on raw text to determine the vocabulary.
  - Intuition: common sequences of characters are represented by a single token, rare sequences are represented by many tokens => improve compression ratio.
  - Training distribution/data matters!

# Byte Pair Encoding



```
def train_bpe(string: str, num_merges: int) -> BPETokenizerParams:  # @inspect string, @inspect num_merges
```

Start with the list of bytes of `string`.

```
    indices = list(map(int, string.encode("utf-8")))  # @inspect indices
    merges: dict[tuple[int, int], int] = {}  # index1, index2 => merged index
    vocab: dict[int, bytes] = {x: bytes([x]) for x in range(256)}  # index -> bytes

    for i in range(num_merges):
```

Count the number of occurrences of each pair of tokens

```
        counts = defaultdict(int)
        for index1, index2 in zip(indices, indices[1:]):  # For each adjacent pair
            counts[(index1, index2)] += 1  # @inspect counts
```

Find the most common pair.

```
        pair = max(counts, key=counts.get)  # @inspect pair
        index1, index2 = pair
```

Merge that pair.

```
        new_index = 256 + i  # @inspect new_index
        merges[pair] = new_index  # @inspect merges
        vocab[new_index] = vocab[index1] + vocab[index2]  # @inspect vocab
        indices = merge(indices, pair, new_index)  # @inspect indices

    return BPETokenizerParams(vocab=vocab, merges=merges)
```

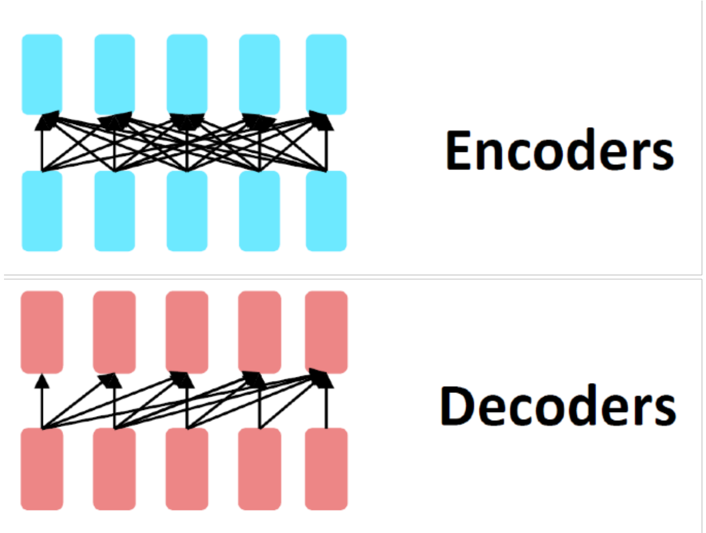
from Stanford CS 336

# Transformer Pre-training

- Collect a large amount of corpus (wiki) and pre-train a large transformer

- For down-stream tasks, fine-tune the pretrained model
  - Or use the pretrained model to extract features

- How to pretrain a transformer on texts?
  - Pretrain an encoder
    - bi-directional
  - Pretrain a decoder
    - auto-regressive

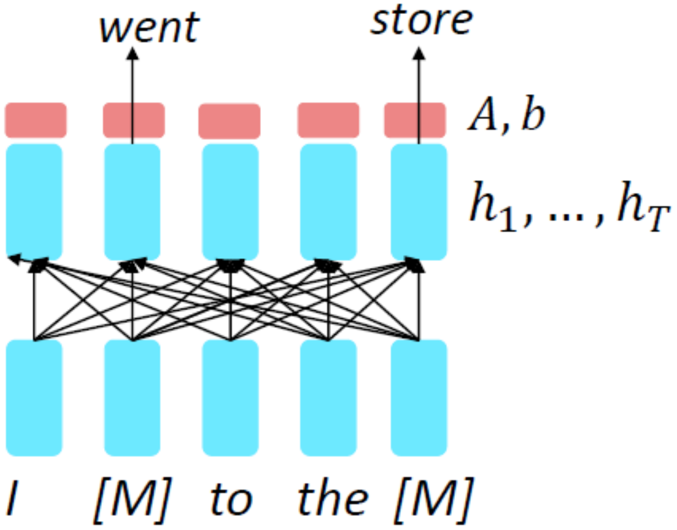


# Pre-training Transformer Encoder

- Pre-training a bi-directional encoder
  - Cannot directly adopt language modeling
  - **Idea:** word prediction given contexts (similar to word2vec)

- Masked language model
  - Randomly "masked out" some words
  - Run full transformer encoder
  - Predict the words at masked positions

- Designed for feature extraction
  - Suitable for down-stream tasks

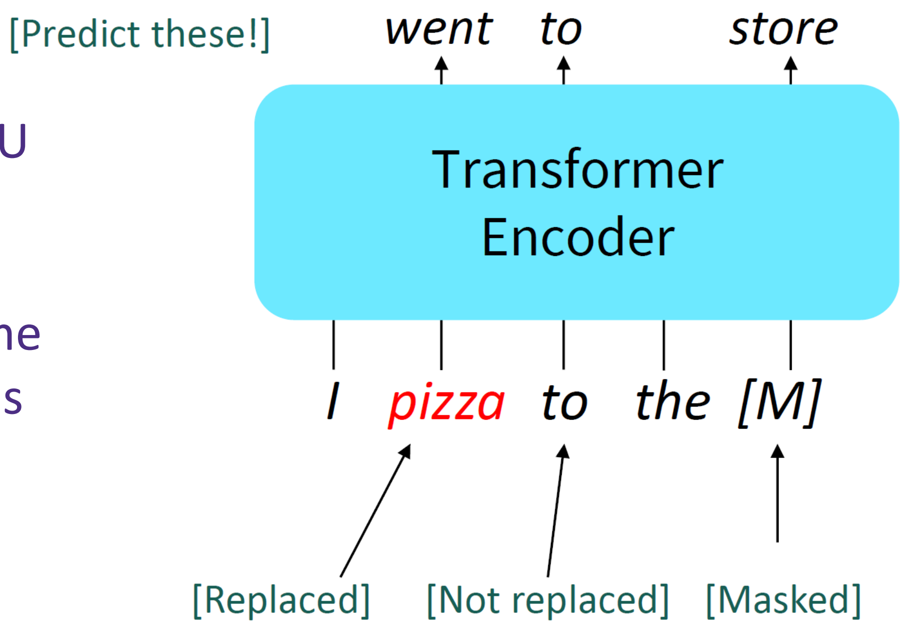


# Pre-training Transformer Encoder

- **BERT:** Pre-training of Deep Bidirectional Transformers

- Devlin et al., Google, 2018
  - BERT-base: 12 layers, 110M params
  - BERT-large: 24 layers, 340M params
  - Training on 64 TPUs in 4 days
  - Fine-tuning can be down in a single GPU

- Masked language model
  - Masked out input words 80% of the time
  - Replace 10% words with random tokens
  - 10% words remain unchanged
  - Predict 15% of word tokens



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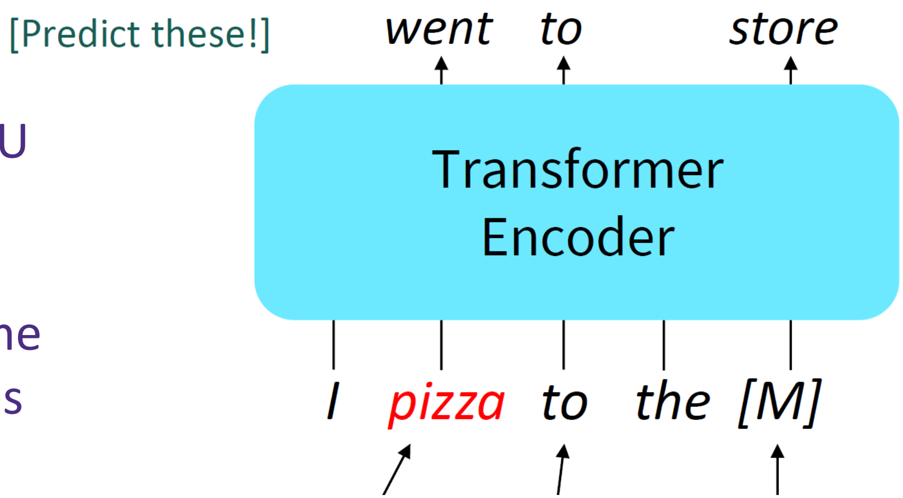
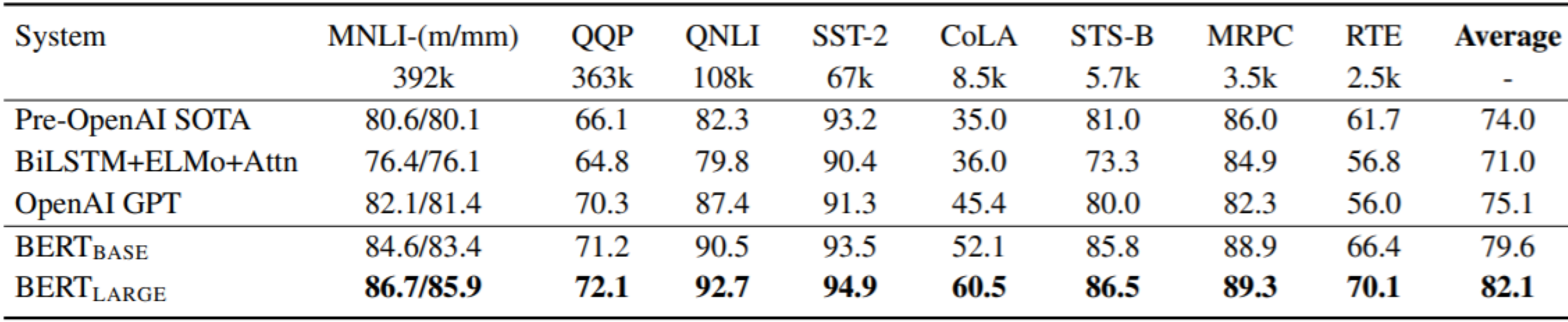


[Predict these!]

*went* *to* *store*

Transformer Encoder

*I* *pizza* *to* *the* *[M]*

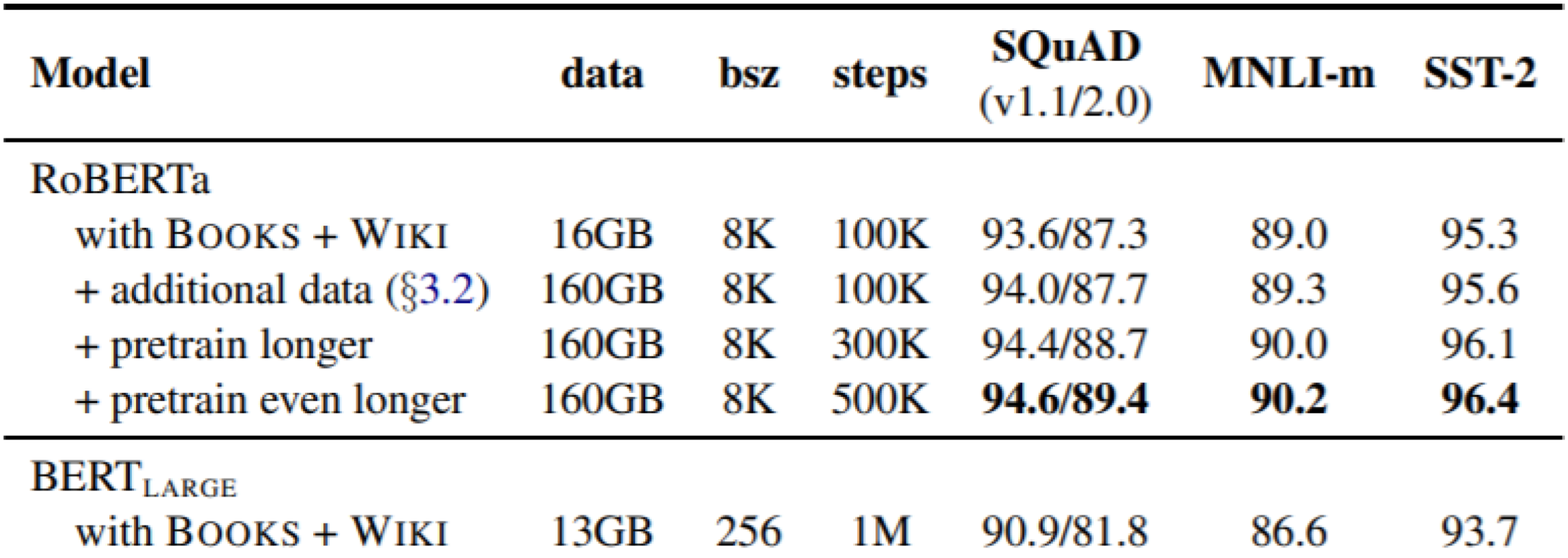


| System | MNLI-(m/mm) | QQP | QNLI | SST-2 | CoLA | STS-B | MRPC | RTE | Average |
|---|---|---|---|---|---|---|---|---|---|
| | 392k | 363k | 108k | 67k | 8.5k | 5.7k | 3.5k | 2.5k | - |
| Pre-OpenAI SOTA | 80.6/80.1 | 66.1 | 82.3 | 93.2 | 35.0 | 81.0 | 86.0 | 61.7 | 74.0 |
| BiLSTM+ELMo+Attn | 76.4/76.1 | 64.8 | 79.8 | 90.4 | 36.0 | 73.3 | 84.9 | 56.8 | 71.0 |
| OpenAI GPT | 82.1/81.4 | 70.3 | 87.4 | 91.3 | 45.4 | 80.0 | 82.3 | 56.0 | 75.1 |
| BERT$_{\text{BASE}}$ | 84.6/83.4 | 71.2 | 90.5 | 93.5 | 52.1 | 85.8 | 88.9 | 66.4 | 79.6 |
| BERT$_{\text{LARGE}}$ | **86.7/85.9** | **72.1** | **92.7** | **94.9** | **60.5** | **86.5** | **89.3** | **70.1** | **82.1** |

# Pre-training Transformer Encoder

- **BERT:** Pre-training of Deep Bidirectional Transformers

- **RoBERTa**: A robustly optimized BERT Pretraining approach
    - Facebook AI and UW, ’19
    - More compute, data, and improved objective



| Model | data | bsz | steps | SQuAD (v1.1/2.0) | MNLI-m | SST-2 |
|---|---|---|---|---|---|---|
| RoBERTa | | | | | | |
| with BOOKS + WIKI | 16GB | 8K | 100K | 93.6/87.3 | 89.0 | 95.3 |
| + additional data (§3.2) | 160GB | 8K | 100K | 94.0/87.7 | 89.3 | 95.6 |
| + pretrain longer | 160GB | 8K | 300K | 94.4/88.7 | 90.0 | 96.1 |
| + pretrain even longer | 160GB | 8K | 500K | **94.6/89.4** | **90.2** | **96.4** |
| BERT$_{\text{LARGE}}$ | | | | | | |
| with BOOKS + WIKI | 13GB | 256 | 1M | 90.9/81.8 | 86.6 | 93.7 |

# Pre-training Decoder

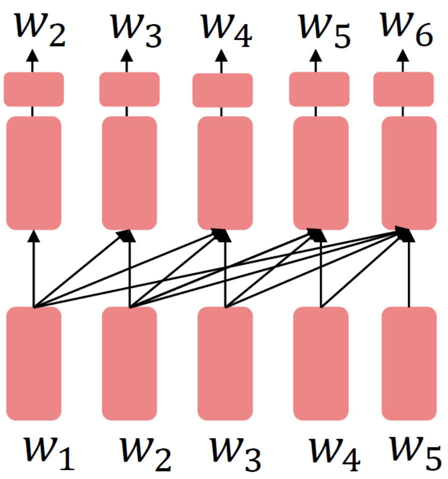
- Decoder Pretraining
  - Just train a language model over corpus.
  - Good for generative task (e.g., text generation)

- Generative Pretrained Transformer (GPT, Open AI ’18)
  - 120 layers transformer, 7680d hidden, 3072-d MLP
  - Data: BooksCropus (>7k books)

- GPT-2 (Radford et al., OpenAI ’19)
  - 1.5B parameters, 40GB internet texts

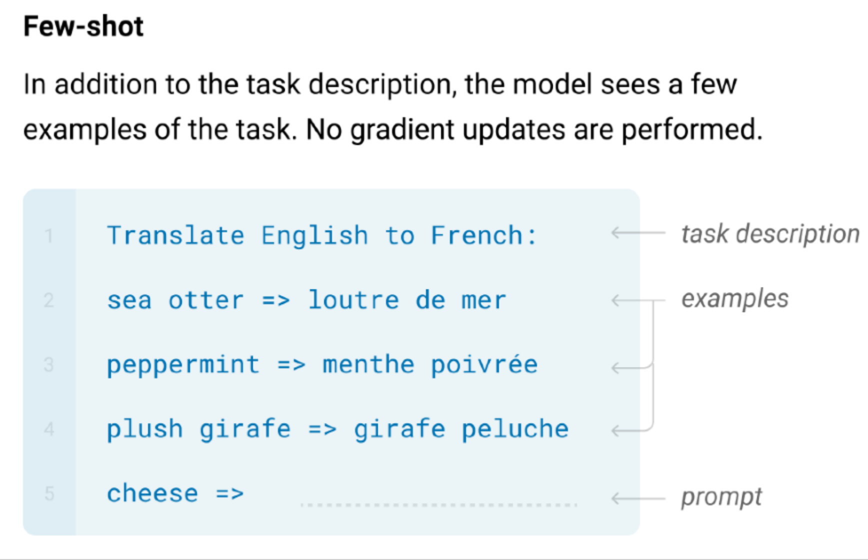
- GPT-3 (OpenAI ’20)
  - Language models are few-shot learners
  - 175B parameters

- Also Image GPT (OpenAI ’20)



# Pre-training Decoder

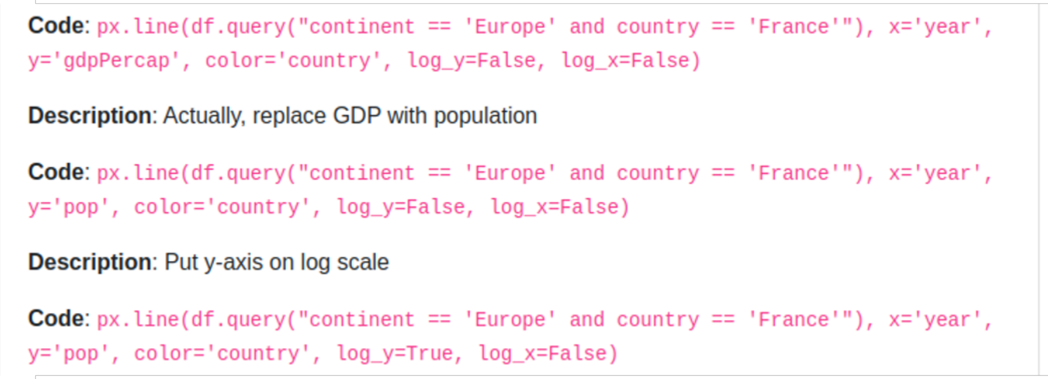
- GPT-3 (OpenAI ’20)
  - You may not need to fine-tune the model parameters for downstream tasks.
  - New paradigm: prompt learning



**Few-shot**

In addition to the task description, the model sees a few examples of the task. No gradient updates are performed.

```
Translate English to French:
sea otter => loutre de mer
peppermint => menthe poivrée
plush girafe => girafe peluche
cheese =>
```



**Code**: `px.line(df.query("continent == 'Europe' and country == 'France'"), x='year', y='gdpPercap', color='country', log_y=False, log_x=False)`

**Description**: Actually, replace GDP with population

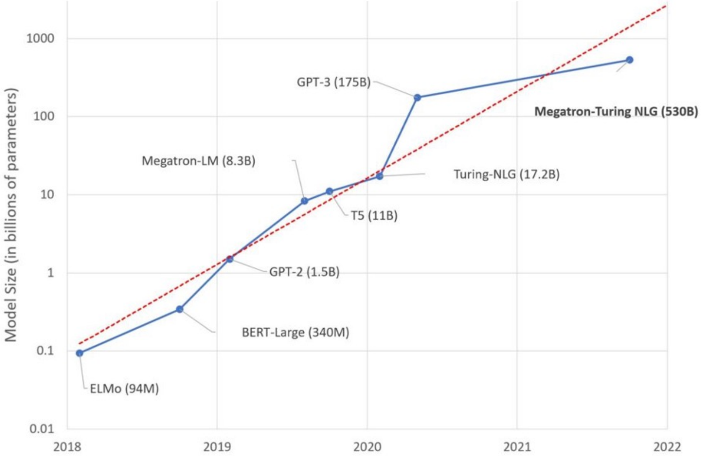
**Code**: `px.line(df.query("continent == 'Europe' and country == 'France'"), x='year', y='pop', color='country', log_y=False, log_x=False)`

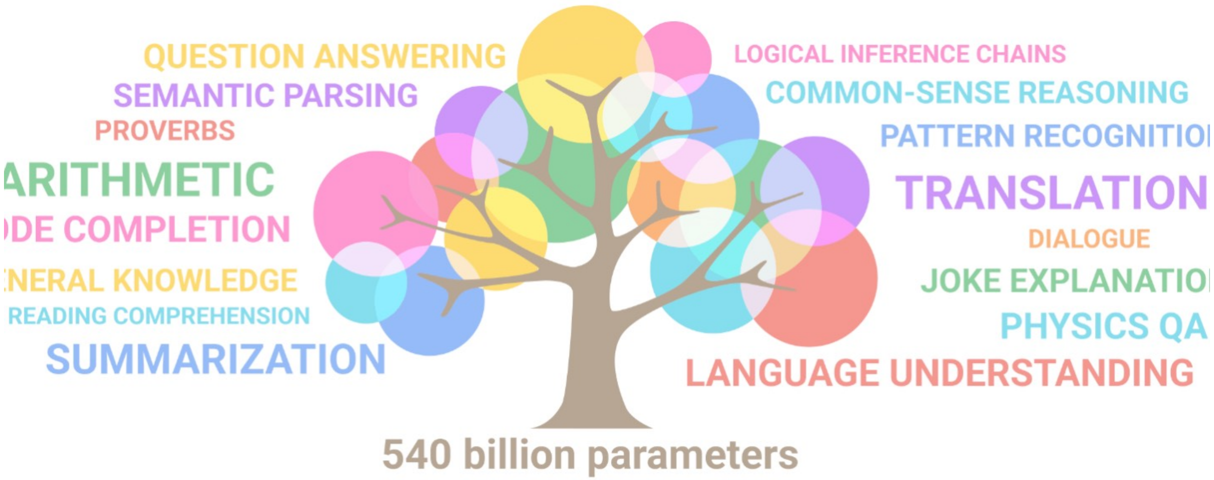
**Description**: Put y-axis on log scale

**Code**: `px.line(df.query("continent == 'Europe' and country == 'France'"), x='year', y='pop', color='country', log_y=True, log_x=False)`

# Pre-training Decoder

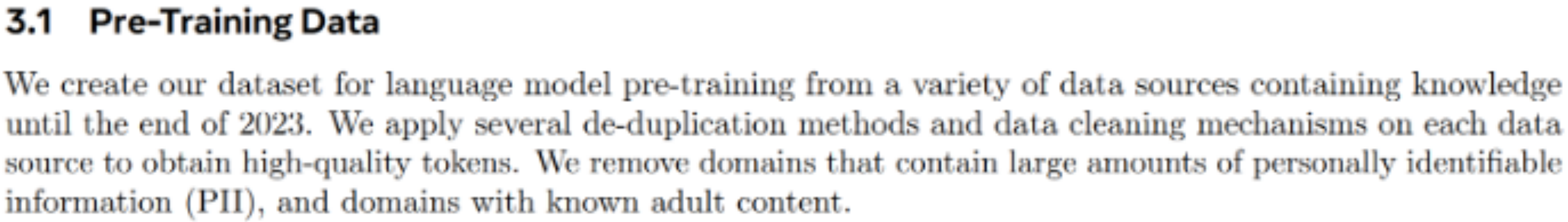
- A big ongoing race on training large language models
  - Megatron-Turing NLG (530B, Microsoft, ’22)
  - Pathways Language Model (540B, Google, ’22)





# Pre-training data

- Data is even more important than architecture / optimizer.
  - Llama 3 has full recipe of architecture and training, but little information about data.

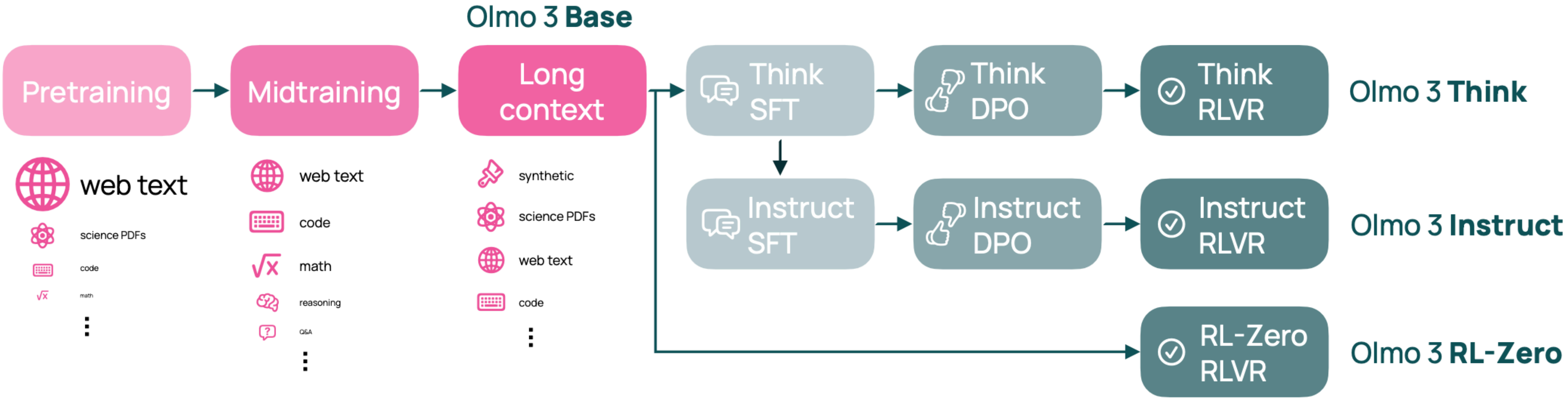


### 3.1 Pre-Training Data

We create our dataset for language model pre-training from a variety of data sources containing knowledge until the end of 2023. We apply several de-duplication methods and data cleaning mechanisms on each data source to obtain high-quality tokens. We remove domains that contain large amounts of personally identifiable information (PII), and domains with known adult content.

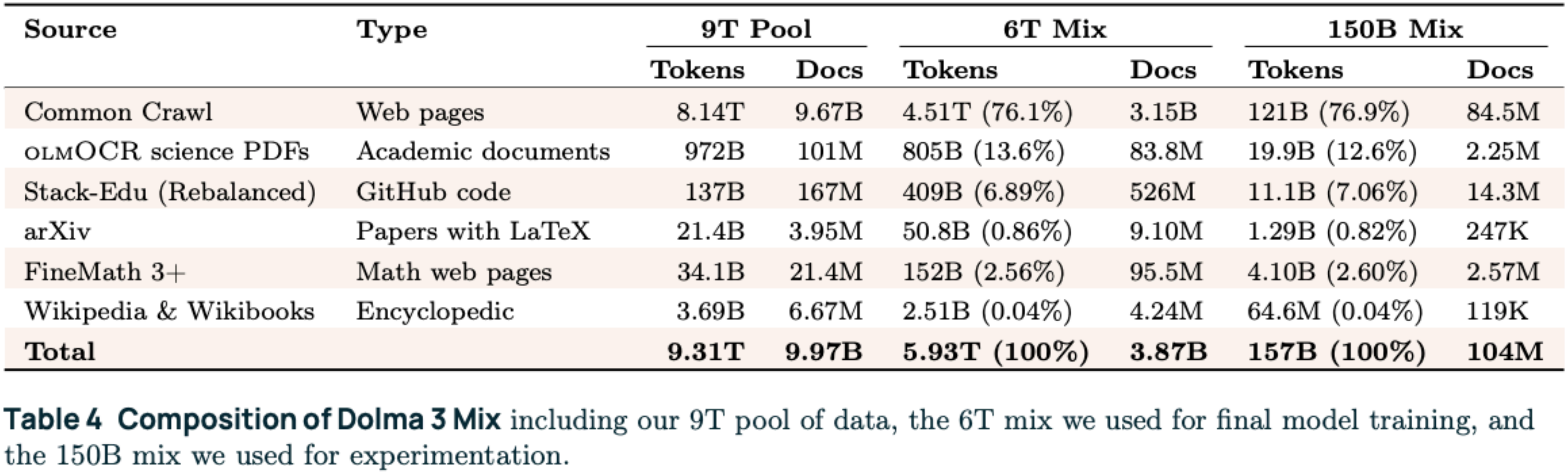
# LLM Pipeline

- Olmo 3
  - Best Open **Recipe** Model: Everything open



# Pre-training data

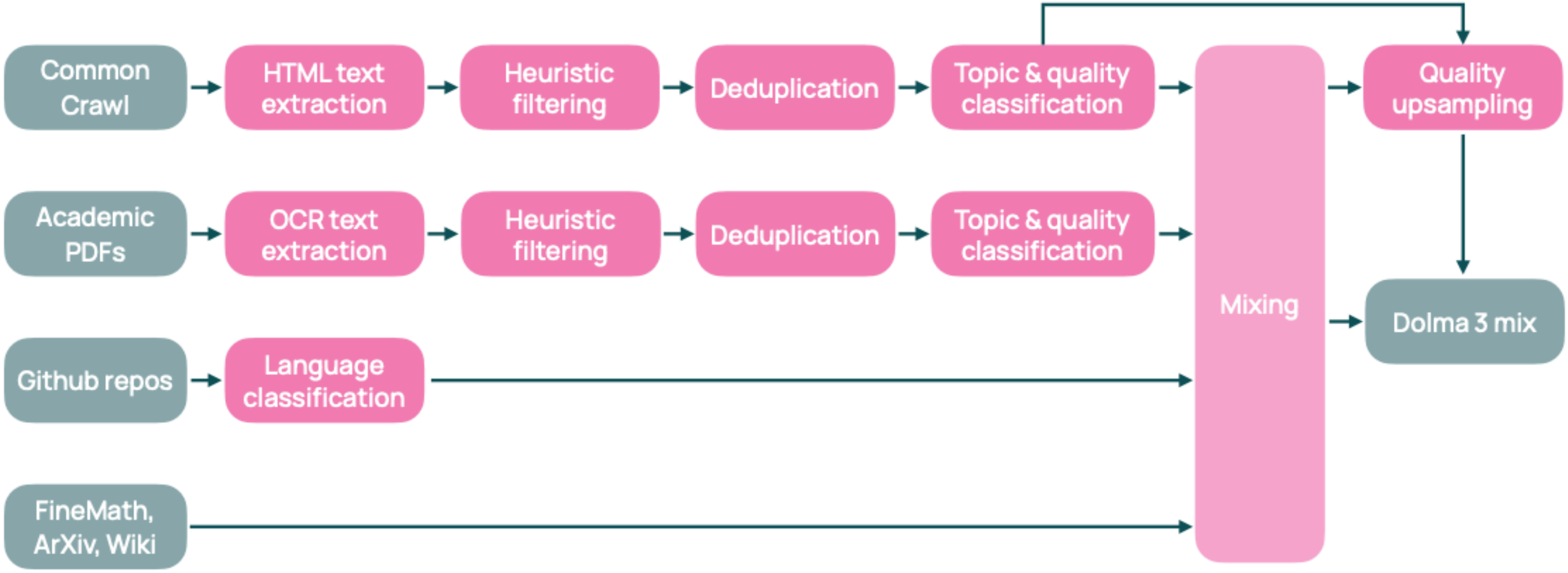
- Pre-training data



| Source | Type | 9T Pool | | 6T Mix | | 150B Mix | |
|---|---|---|---|---|---|---|---|
| | | Tokens | Docs | Tokens | Docs | Tokens | Docs |
| Common Crawl | Web pages | 8.14T | 9.67B | 4.51T (76.1%) | 3.15B | 121B (76.9%) | 84.5M |
| olmOCR science PDFs | Academic documents | 972B | 101M | 805B (13.6%) | 83.8M | 19.9B (12.6%) | 2.25M |
| Stack-Edu (Rebalanced) | GitHub code | 137B | 167M | 409B (6.89%) | 526M | 11.1B (7.06%) | 14.3M |
| arXiv | Papers with LaTeX | 21.4B | 3.95M | 50.8B (0.86%) | 9.10M | 1.29B (0.82%) | 247K |
| FineMath 3+ | Math web pages | 34.1B | 21.4M | 152B (2.56%) | 95.5M | 4.10B (2.60%) | 2.57M |
| Wikipedia & Wikibooks | Encyclopedic | 3.69B | 6.67M | 2.51B (0.04%) | 4.24M | 64.6M (0.04%) | 119K |
| **Total** | | **9.31T** | **9.97B** | **5.93T (100%)** | **3.87B** | **157B (100%)** | **104M** |

**Table 4 Composition of Dolma 3 Mix** including our 9T pool of data, the 6T mix we used for final model training, and the 150B mix we used for experimentation.

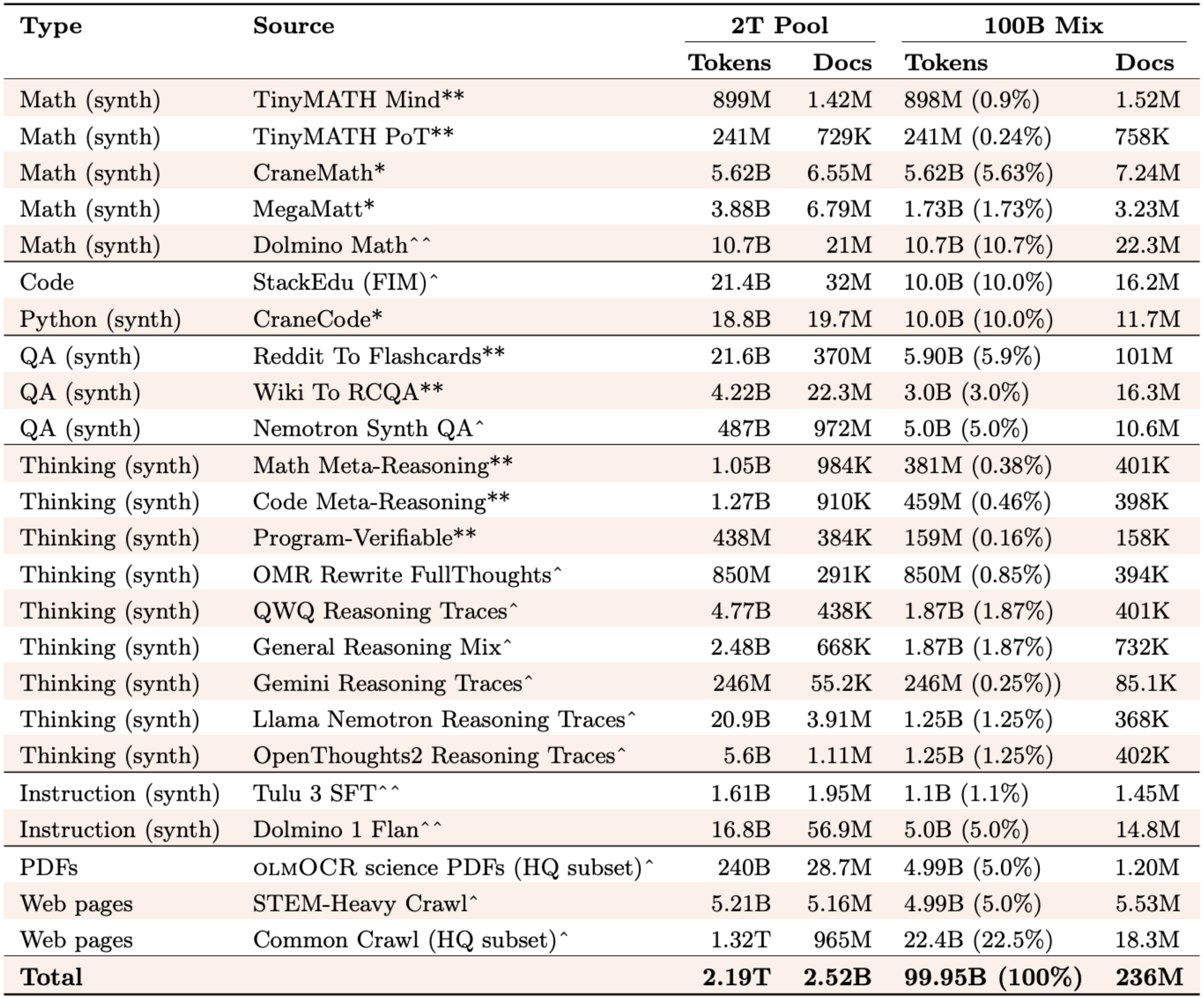
# Pre-training data



- Heuristic filtering: spam filtering, excessive symbols, sentence too short, etc…
- Deduplication: min-hash, fuzzy duplicate removal
- Classification: topic classification, whether useful or not (fastText classifier), etc
- Mixing: every document has topic label and quality score, balance topic, upweight quality

# Mid-training Data

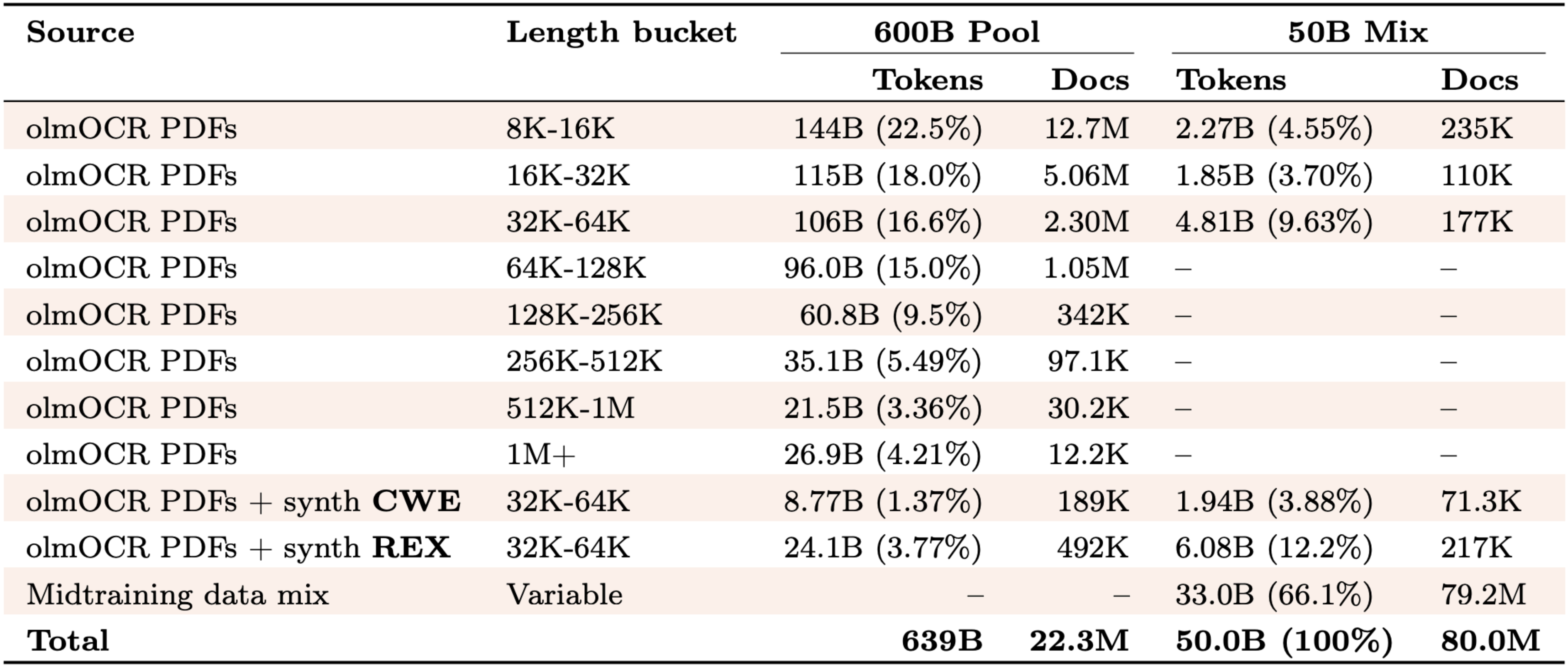
- Improve some fundamental capabilities (higher quality data)



| Type | Source | 2T Pool | | 100B Mix | |
|---|---|---|---|---|---|
| | | Tokens | Docs | Tokens | Docs |
| Math (synth) | TinyMATH Mind** | 899M | 1.42M | 898M (0.9%) | 1.52M |
| Math (synth) | TinyMATH PoT** | 241M | 729K | 241M (0.24%) | 758K |
| Math (synth) | CraneMath* | 5.62B | 6.55M | 5.62B (5.63%) | 7.24M |
| Math (synth) | MegaMatt* | 3.88B | 6.79M | 1.73B (1.73%) | 3.23M |
| Math (synth) | Dolmino Math^^ | 10.7B | 21M | 10.7B (10.7%) | 22.3M |
| Code | StackEdu (FIM)^ | 21.4B | 32M | 10.0B (10.0%) | 16.2M |
| Python (synth) | CraneCode* | 18.8B | 19.7M | 10.0B (10.0%) | 11.7M |
| QA (synth) | Reddit To Flashcards** | 21.6B | 370M | 5.90B (5.9%) | 101M |
| QA (synth) | Wiki To RCQA** | 4.22B | 22.3M | 3.0B (3.0%) | 16.3M |
| QA (synth) | Nemotron Synth QA^ | 487B | 972M | 5.0B (5.0%) | 10.6M |
| Thinking (synth) | Math Meta-Reasoning** | 1.05B | 984K | 381M (0.38%) | 401K |
| Thinking (synth) | Code Meta-Reasoning** | 1.27B | 910K | 459M (0.46%) | 398K |
| Thinking (synth) | Program-Verifiable** | 438M | 384K | 159M (0.16%) | 158K |
| Thinking (synth) | OMR Rewrite FullThoughts^ | 850M | 291K | 850M (0.85%) | 394K |
| Thinking (synth) | QWQ Reasoning Traces^ | 4.77B | 438K | 1.87B (1.87%) | 401K |
| Thinking (synth) | General Reasoning Mix^ | 2.48B | 668K | 1.87B (1.87%) | 732K |
| Thinking (synth) | Gemini Reasoning Traces^ | 246M | 55.2K | 246M (0.25%)) | 85.1K |
| Thinking (synth) | Llama Nemotron Reasoning Traces^ | 20.9B | 3.91M | 1.25B (1.25%) | 368K |
| Thinking (synth) | OpenThoughts2 Reasoning Traces^ | 5.6B | 1.11M | 1.25B (1.25%) | 402K |
| Instruction (synth) | Tulu 3 SFT^^ | 1.61B | 1.95M | 1.1B (1.1%) | 1.45M |
| Instruction (synth) | Dolmino 1 Flan^^ | 16.8B | 56.9M | 5.0B (5.0%) | 14.8M |
| PDFs | olmOCR science PDFs (HQ subset)^ | 240B | 28.7M | 4.99B (5.0%) | 1.20M |
| Web pages | STEM-Heavy Crawl^ | 5.21B | 5.16M | 4.99B (5.0%) | 5.53M |
| Web pages | Common Crawl (HQ subset)^ | 1.32T | 965M | 22.4B (22.5%) | 18.3M |
| **Total** | | **2.19T** | **2.52B** | **99.95B (100%)** | **236M** |

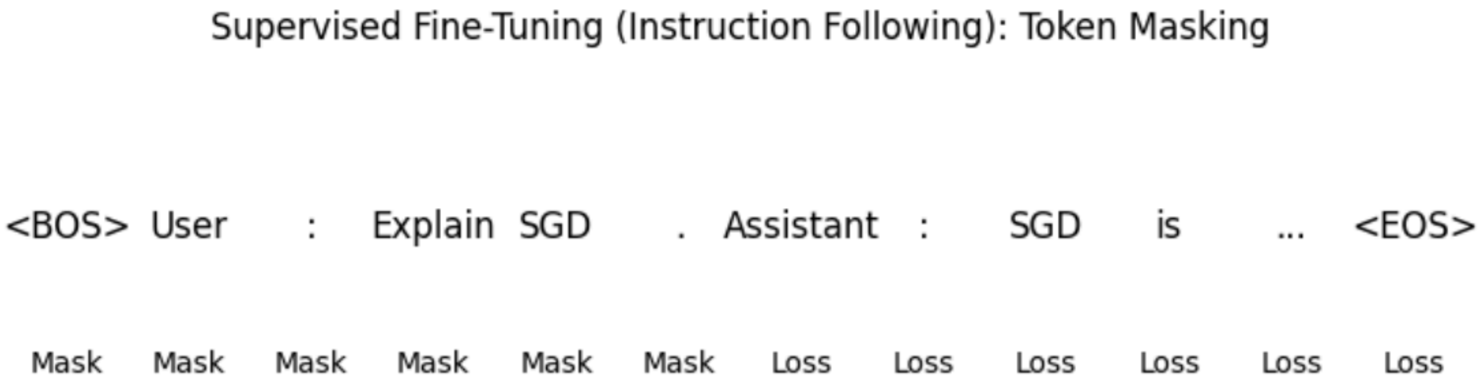
# Long-context Extension

- Extend context window from 8k to 64k



| Source | Length bucket | 600B Pool | | 50B Mix | |
|---|---|---|---|---|---|
| | | Tokens | Docs | Tokens | Docs |
| olmOCR PDFs | 8K-16K | 144B (22.5%) | 12.7M | 2.27B (4.55%) | 235K |
| olmOCR PDFs | 16K-32K | 115B (18.0%) | 5.06M | 1.85B (3.70%) | 110K |
| olmOCR PDFs | 32K-64K | 106B (16.6%) | 2.30M | 4.81B (9.63%) | 177K |
| olmOCR PDFs | 64K-128K | 96.0B (15.0%) | 1.05M | – | – |
| olmOCR PDFs | 128K-256K | 60.8B (9.5%) | 342K | – | – |
| olmOCR PDFs | 256K-512K | 35.1B (5.49%) | 97.1K | – | – |
| olmOCR PDFs | 512K-1M | 21.5B (3.36%) | 30.2K | – | – |
| olmOCR PDFs | 1M+ | 26.9B (4.21%) | 12.2K | – | – |
| olmOCR PDFs + synth **CWE** | 32K-64K | 8.77B (1.37%) | 189K | 1.94B (3.88%) | 71.3K |
| olmOCR PDFs + synth **REX** | 32K-64K | 24.1B (3.77%) | 492K | 6.08B (12.2%) | 217K |
| Midtraining data mix | Variable | – | – | 33.0B (66.1%) | 79.2M |
| **Total** | | **639B** | **22.3M** | **50.0B (100%)** | **80.0M** |

# Supervised Fine-Tuning

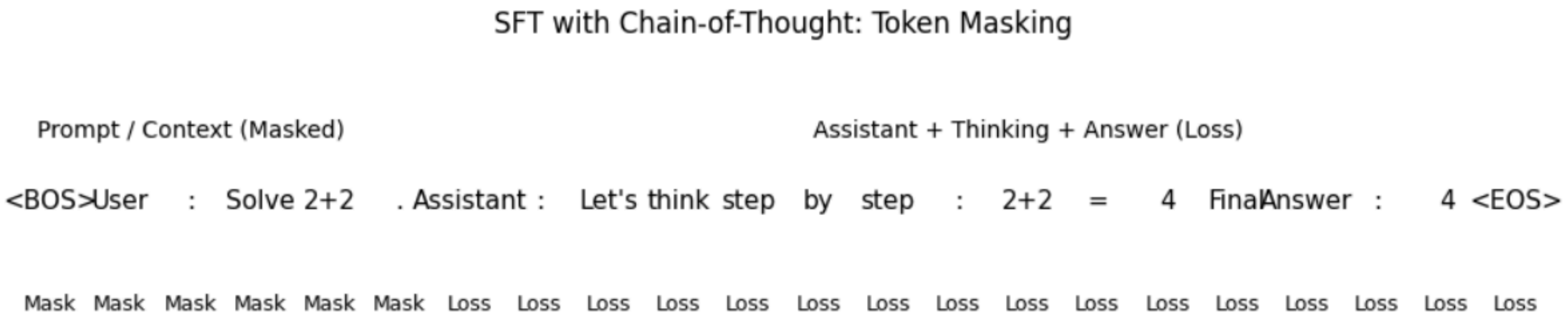


Supervised Fine-Tuning (Instruction Following): Token Masking

| <BOS> | User | : | Explain | SGD | . | Assistant | : | SGD | is | ... | <EOS> |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Mask | Mask | Mask | Mask | Mask | Mask | Loss | Loss | Loss | Loss | Loss | Loss |

- Do not train on masked tokens.
- Data format: prompt, response.

# Supervised Fine-Tuning with Thinking



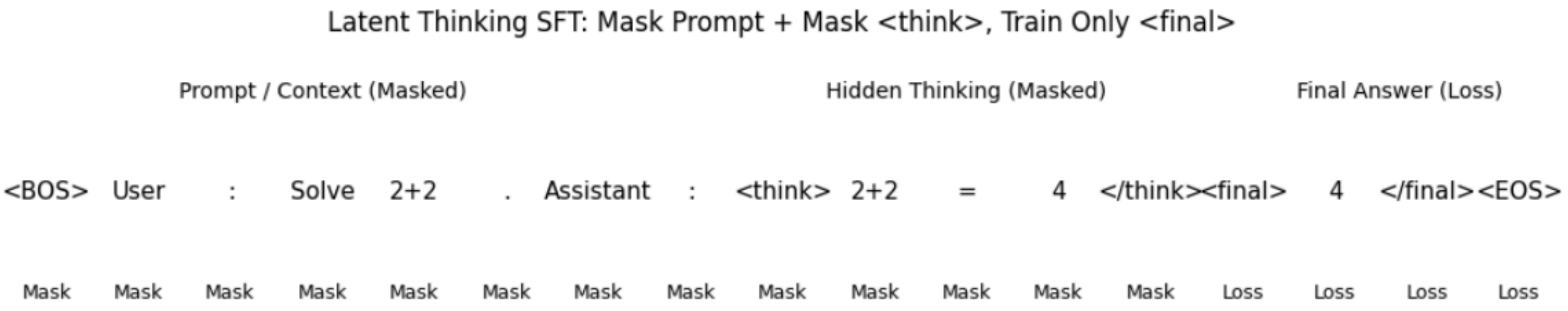
SFT with Chain-of-Thought: Token Masking

Prompt / Context (Masked)

Assistant + Thinking + Answer (Loss)

| | | | | | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| <BOS> | User | : | Solve | 2+2 | . | Assistant | : | Let's | think | step | by | step | : | 2+2 | = | 4 | Final | Answer | : | 4 | <EOS> |
| Mask | Mask | Mask | Mask | Mask | Mask | Loss | Loss | Loss | Loss | Loss | Loss | Loss | Loss | Loss | Loss | Loss | Loss | Loss | Loss | Loss | Loss |

- Chain-of-Thought: COT.



Latent Thinking SFT: Mask Prompt + Mask <think>, Train Only <final>

Prompt / Context (Masked)

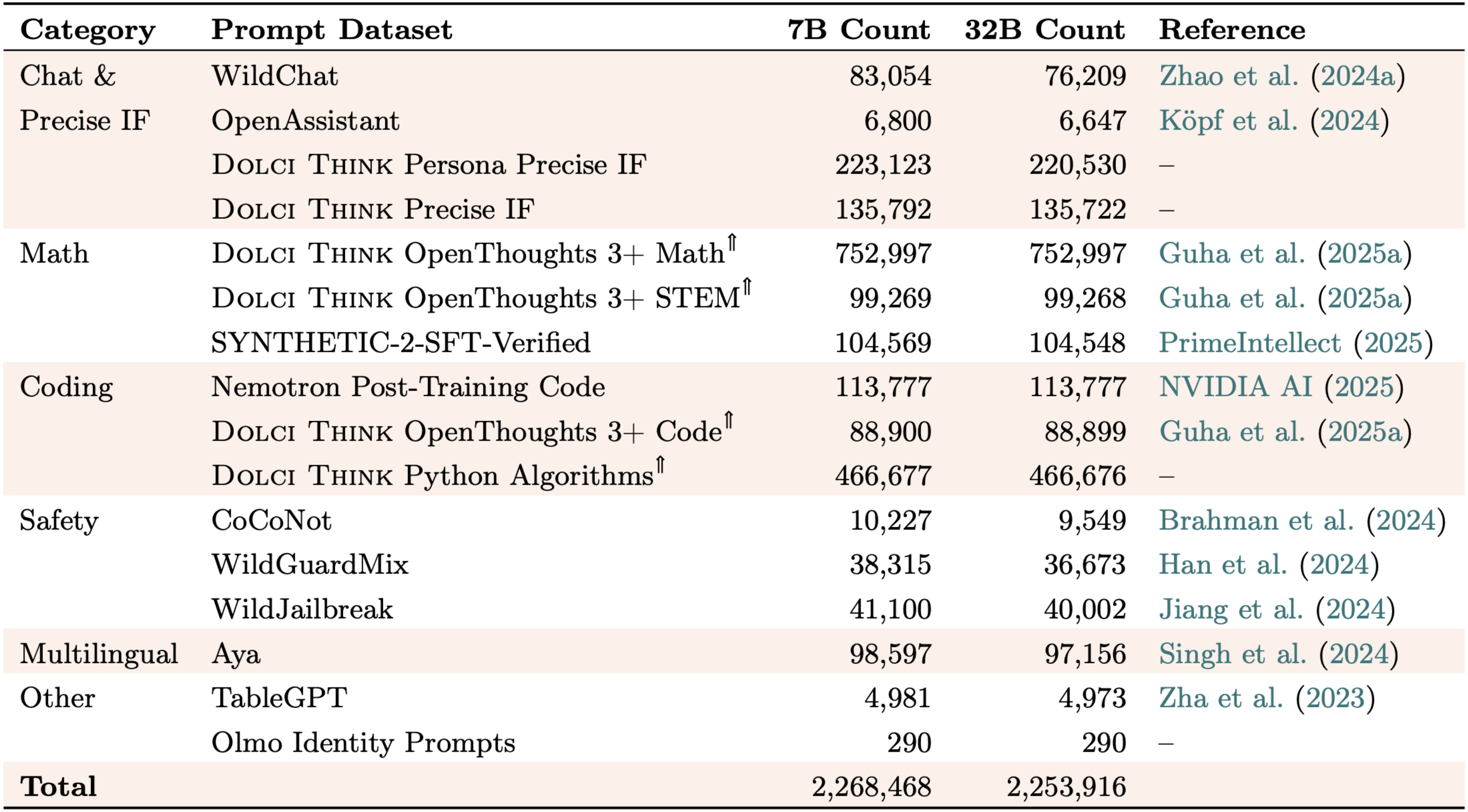
Hidden Thinking (Masked)

Final Answer (Loss)

| | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| <BOS> | User | : | Solve | 2+2 | . | Assistant | : | <think> | 2+2 | = | 4 | </think> | <final> | 4 | </final> | <EOS> |
| Mask | Mask | Mask | Mask | Mask | Mask | Mask | Mask | Mask | Mask | Mask | Mask | Mask | Loss | Loss | Loss | Loss |

# SFT Data

- High quality.



| Category | Prompt Dataset | 7B Count | 32B Count | Reference |
|---|---|---|---|---|
| Chat & | WildChat | 83,054 | 76,209 | Zhao et al. (2024a) |
| Precise IF | OpenAssistant | 6,800 | 6,647 | Köpf et al. (2024) |
| | Dolci Think Persona Precise IF | 223,123 | 220,530 | – |
| | Dolci Think Precise IF | 135,792 | 135,722 | – |
| Math | Dolci Think OpenThoughts 3+ Math⇑ | 752,997 | 752,997 | Guha et al. (2025a) |
| | Dolci Think OpenThoughts 3+ STEM⇑ | 99,269 | 99,268 | Guha et al. (2025a) |
| | SYNTHETIC-2-SFT-Verified | 104,569 | 104,548 | PrimeIntellect (2025) |
| Coding | Nemotron Post-Training Code | 113,777 | 113,777 | NVIDIA AI (2025) |
| | Dolci Think OpenThoughts 3+ Code⇑ | 88,900 | 88,899 | Guha et al. (2025a) |
| | Dolci Think Python Algorithms⇑ | 466,677 | 466,676 | – |
| Safety | CoCoNot | 10,227 | 9,549 | Brahman et al. (2024) |
| | WildGuardMix | 38,315 | 36,673 | Han et al. (2024) |
| | WildJailbreak | 41,100 | 40,002 | Jiang et al. (2024) |
| Multilingual | Aya | 98,597 | 97,156 | Singh et al. (2024) |
| Other | TableGPT | 4,981 | 4,973 | Zha et al. (2023) |
| | Olmo Identity Prompts | 290 | 290 | – |
| **Total** | | 2,268,468 | 2,253,916 | |

# Parameter-Efficient Fine-Tuning

**LoRA: Low-Rank Adaptation of Large Language Models**
(Hu et al. 2021)

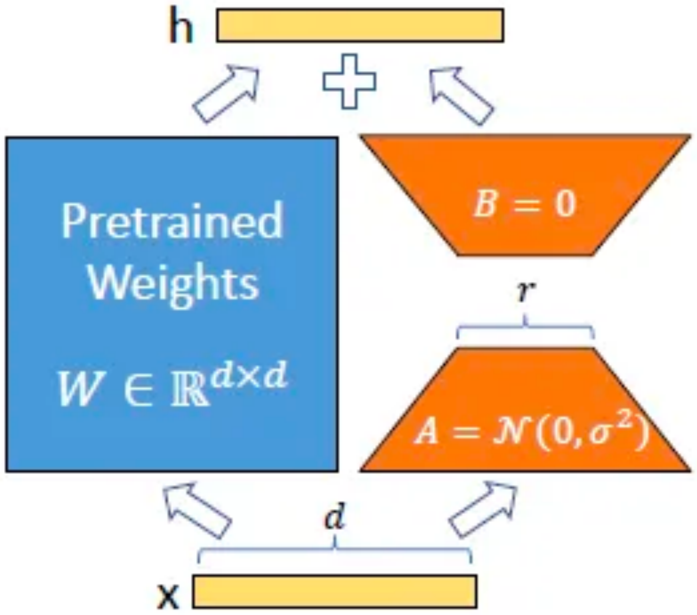
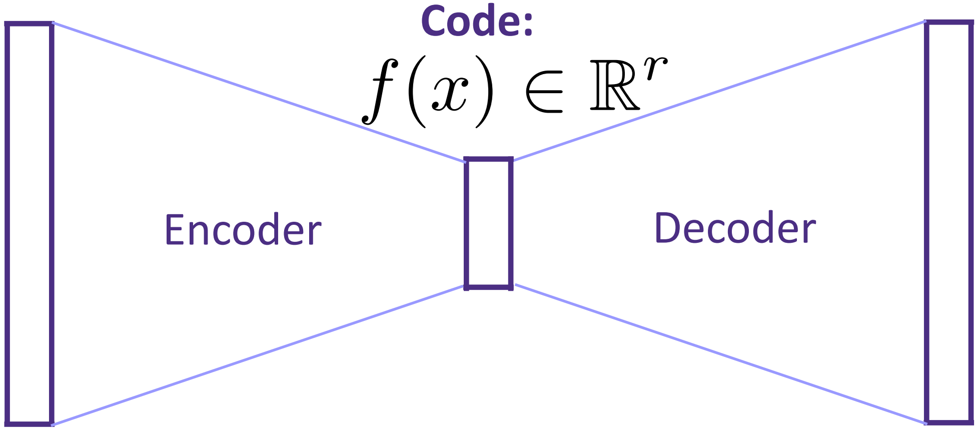

h
Pretrained Weights
$W \in \mathbb{R}^{d \times d}$
$B = 0$
$r$
$A = \mathcal{N}(0, \sigma^2)$
$d$
x

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

# Pre-training Learning Methods for Vision

# Autoencoders

Find a low dimensional representation for your data by predicting your data



**Input:**
$x \in \mathbb{R}^d$

Encoder

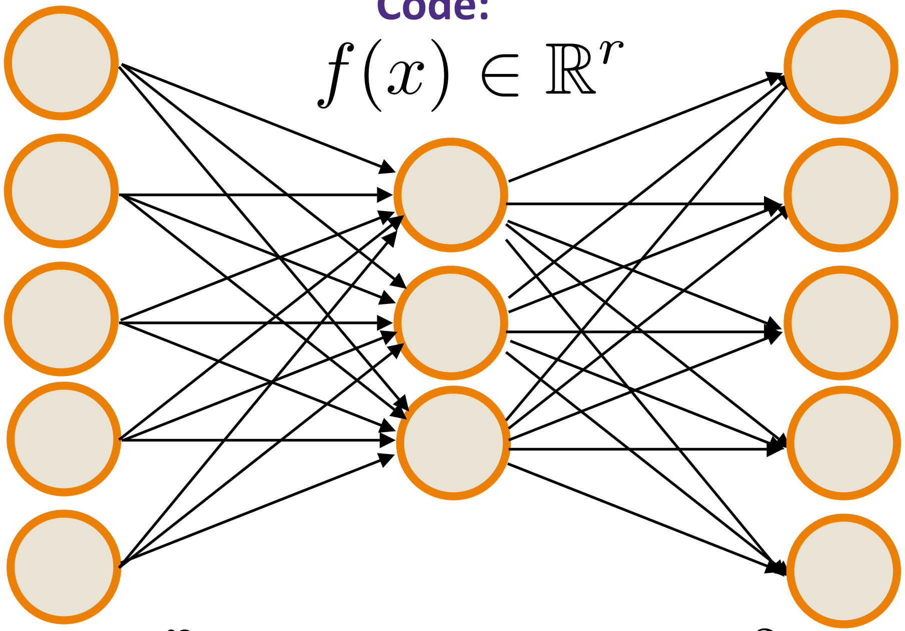
**Code:**
$f(x) \in \mathbb{R}^r$

Decoder

**Output:**
$\widehat{x} = g(f(x)) \in \mathbb{R}^d$

$$\underset{f,g}{\text{minimize}} \sum_{i=1}^{n} \|x_i - g(f(x_i))\|_2^2$$

# Autoencoders



**Input:**
$x \in \mathbb{R}^d$

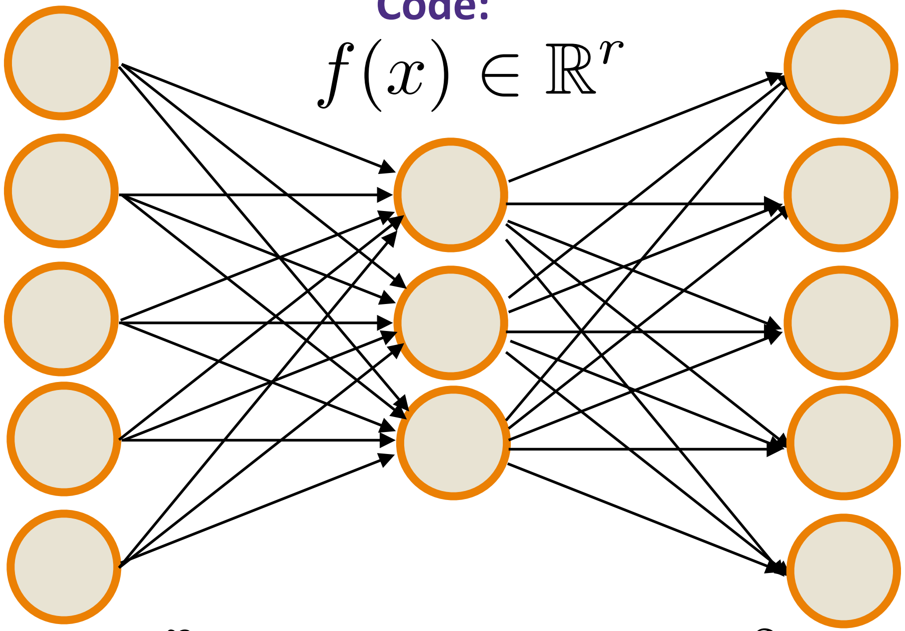
**Code:**
$f(x) \in \mathbb{R}^r$

**Output:**
$\widehat{x} = g(f(x)) \in \mathbb{R}^d$

$$\underset{f,g}{\text{minimize}} \sum_{i=1}^{n} \|x_i - g(f(x_i))\|_2^2$$

What if $f(X) = Ax$ and $g(y) = By$?

# Autoencoders



**Code:**

$f(x) \in \mathbb{R}^r$

**Input:**

$x \in \mathbb{R}^d$

**Output:**

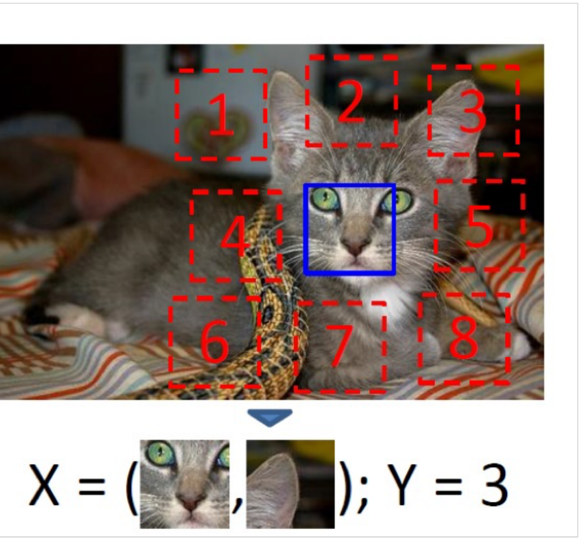
$\widehat{x} = g(f(x)) \in \mathbb{R}^d$

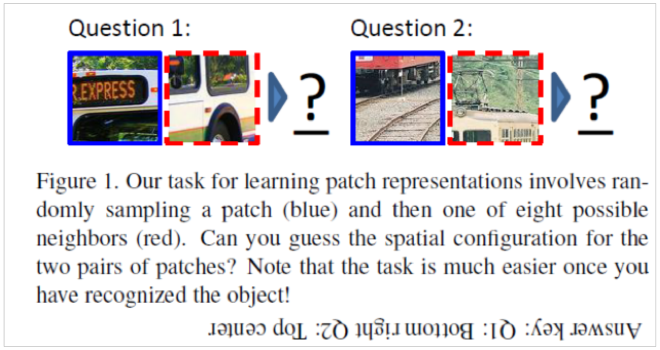
$$\underset{f,g}{\text{minimize}} \sum_{i=1}^{n} \|x_i - g(f(x_i))\|_2^2$$

What if $f(X) = Ax$ and $g(y) = By$?

# Self-supervised learning in computer vision

## **Context Prediction** (Pathak et al., '15)

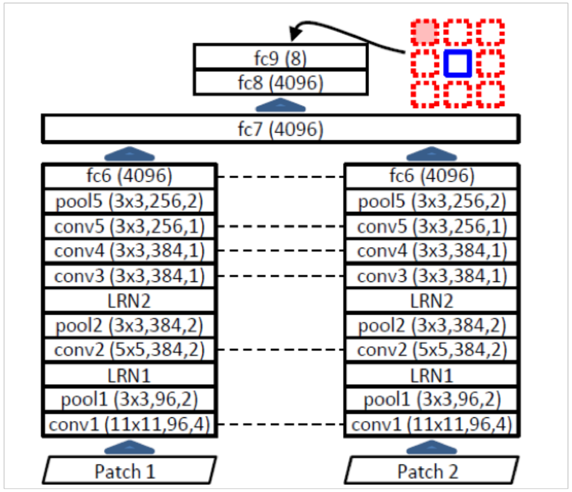


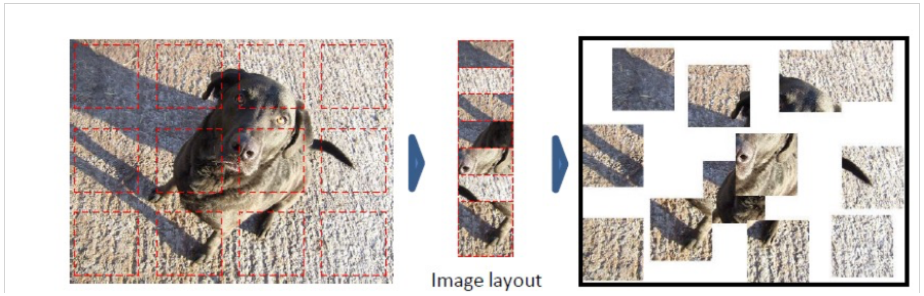


Question 1:
Question 2:
?
?

Figure 1. Our task for learning patch representations involves randomly sampling a patch (blue) and then one of eight possible neighbors (red). Can you guess the spatial configuration for the two pairs of patches? Note that the task is much easier once you have recognized the object!

Answer key: Q1: Bottom right Q2: Top center





# Self-supervised learning in computer vision

- **Feature learning by Inpainting** (Pathak et al., ’16)
  - The most obvious analogue to word embeddings: predict parts of image from the remainder of image

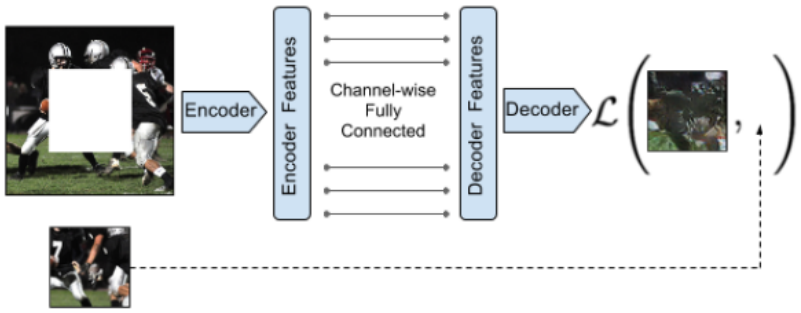


Figure 2: Context Encoder. The context image is passed through the encoder to obtain features which are connected to the decoder using channel-wise fully-connected layer as described in Section 3.1. The decoder then produces the missing regions in the image.

Architectures:
An encoder takes a part of an image, constructs a representation.

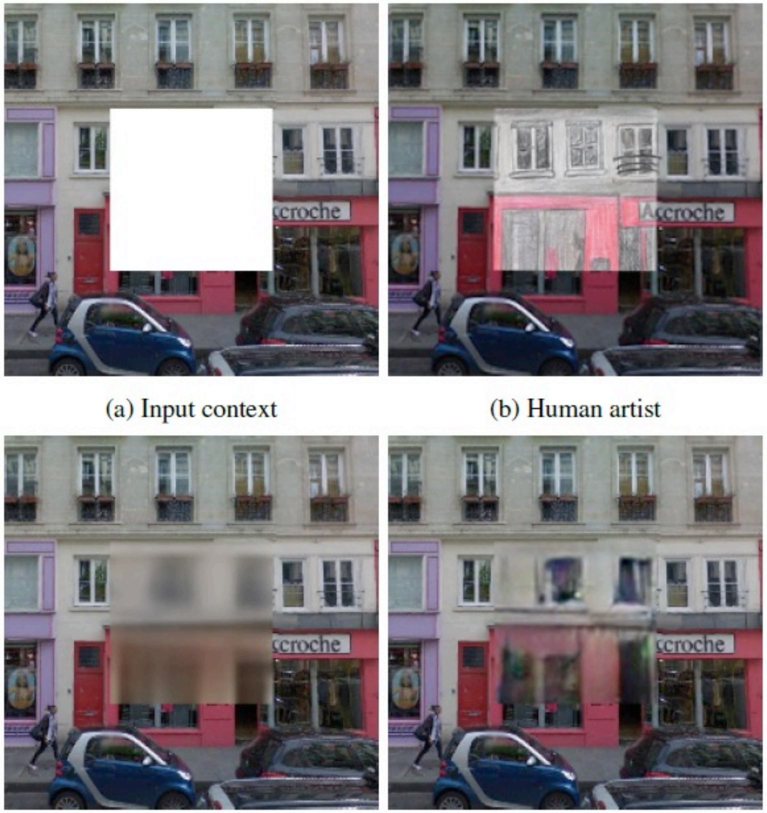
A decoder takes the representation, tries to reconstruct the missing part.

Trickier than NLP:

1. Meaningful losses for vision are more difficult to design.
2. Choice of region to mask out is important

# Self-supervised learning in computer vision

- **Feature learning by Inpainting** (Pathak et al., ’16)



(a) Input context

(b) Human artist

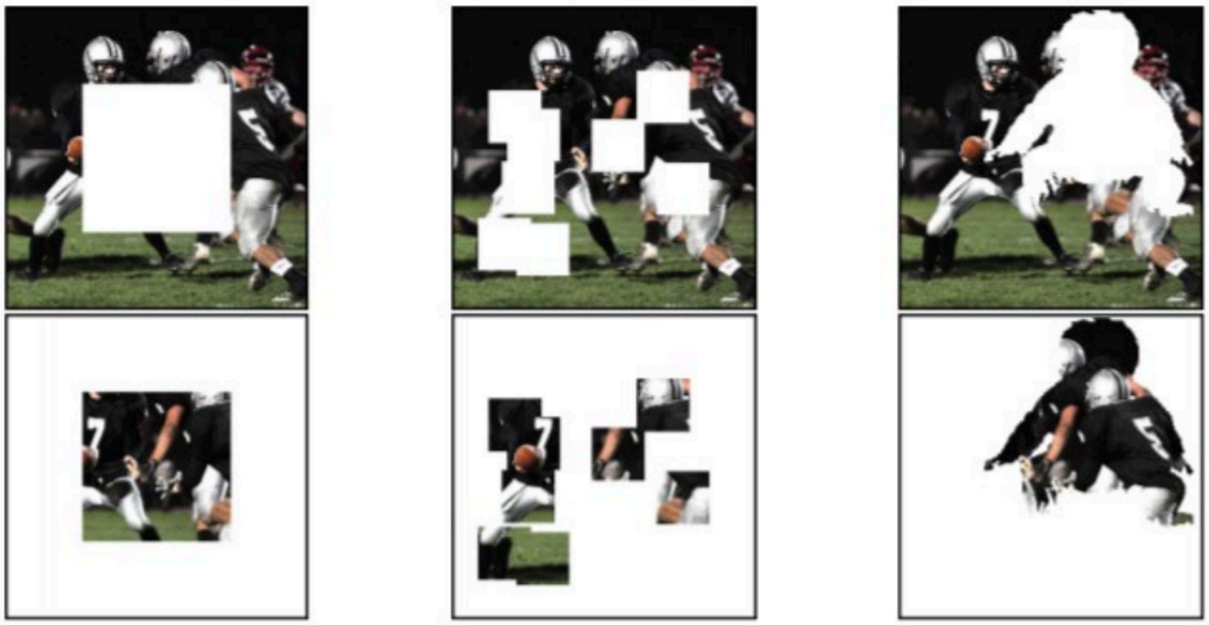
(c) Context Encoder
($L2$ loss)

(d) Context Encoder
($L2$ + Adversarial loss)

$L_2$ vs. Adversarial loss

# Self-supervised learning in computer vision

- **Feature learning by Inpainting** (Pathak et al., ’16)



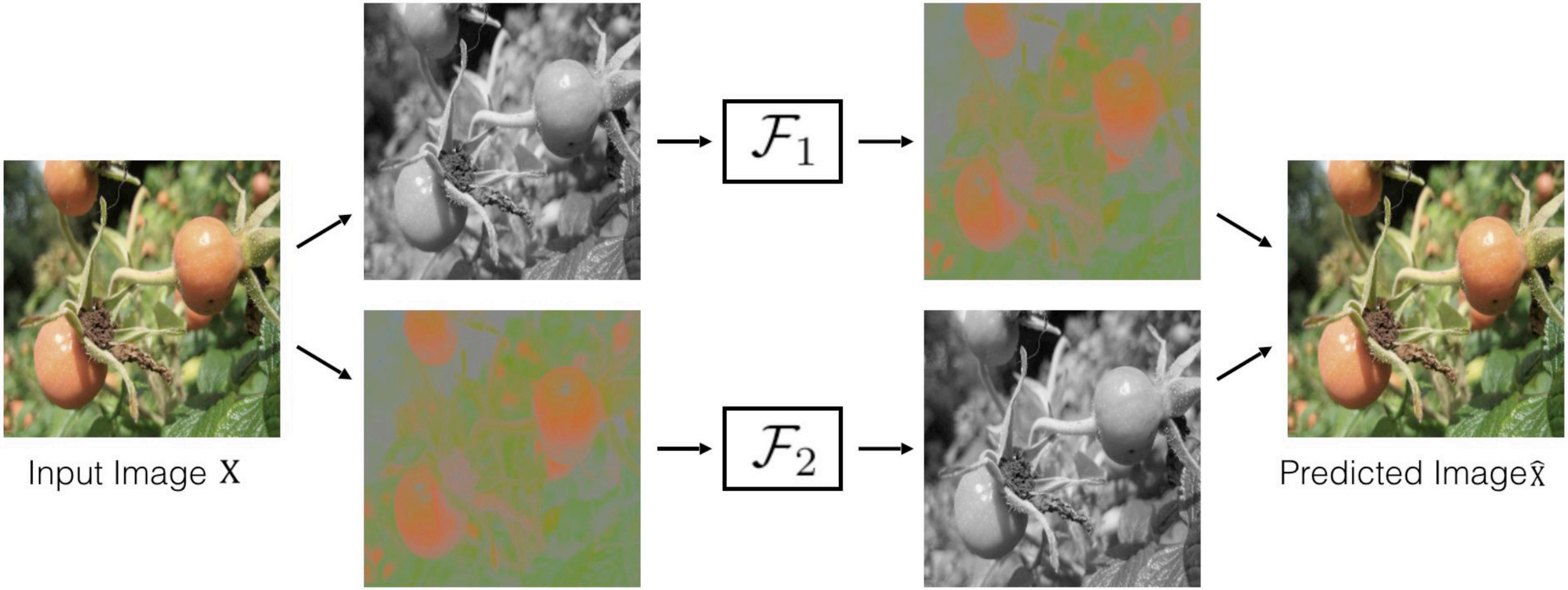
(a) Central region (b) Random block (c) Random region

Figure 3: An example of image $x$ with our different region masks $\hat{M}$ applied, as described in Section 3.3.

Fixed region vs. random square block vs. random region

# Self-supervised learning in computer vision

- **Image Colorization** (Zhang et al. ’16)



# Self-supervised learning in computer vision

- **Rotation Prediction** (Gidaris et al., ’18)

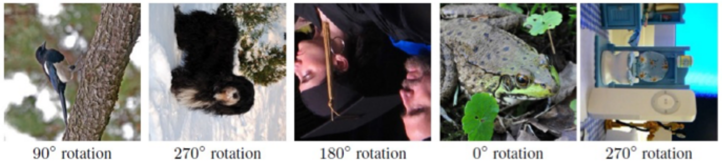
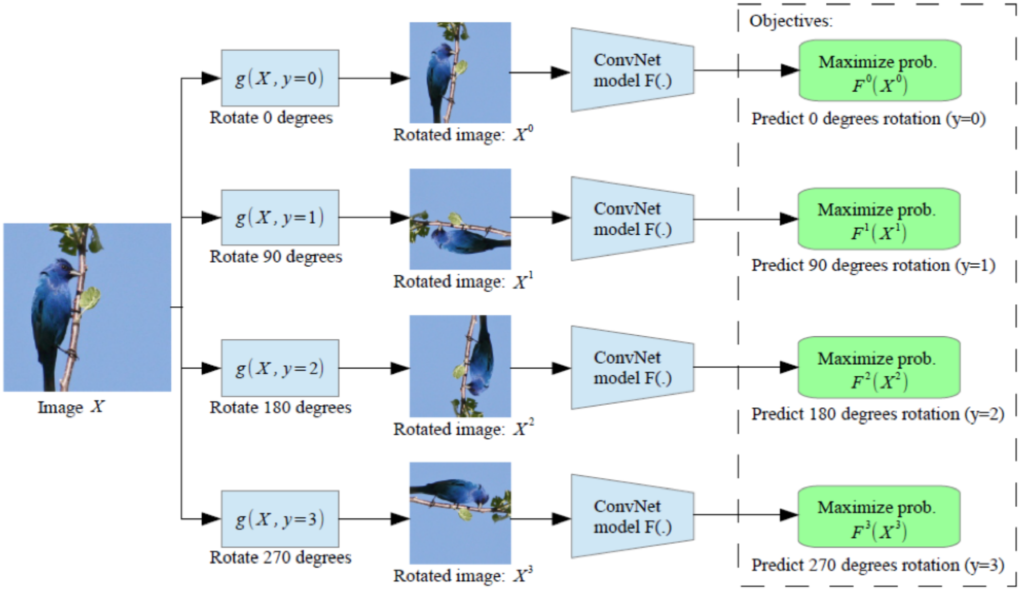


Figure 1: Images rotated by random multiples of 90 degrees (e.g., 0, 90, 180, or 270 degrees). The core intuition of our self-supervised feature learning approach is that if someone is not aware of the concepts of the objects depicted in the images, he cannot recognize the rotation that was applied to them.

(a) **Attention maps of supervised model** (b) **Attention maps of our self-supervised model**



# Contrastive learning

**Idea:** if features are "semantically" relevant, a "distortion" of an image should produce similar features.

**Framework:**

- For every training sample, produce multiple *augmented* samples by applying various transformations.
- Train an encoder ***E*** to predict whether two samples are augmentations of the same base sample.
- A common way is train $\langle E(x), E(x') \rangle$ big if $x, x'$ are two augmentations of the same sample:

$$\ell_{x,x'} = -\log\left(\frac{\exp(\tau\langle E(x), E(x')\rangle)}{\sum_{\tilde{x}} \exp(\tau\langle E(x), E(\tilde{x})\rangle)}\right)$$

$$\min \sum_{x,x' \text{ augments of each other}} \ell_{x,x'}$$

# Contrastive learning

**Contrastive Predictive Coding** (Van den Oord et al., ’18)

- CPC: Original proposed on audio data
- Use context to predict futures
  - Random negative samples required

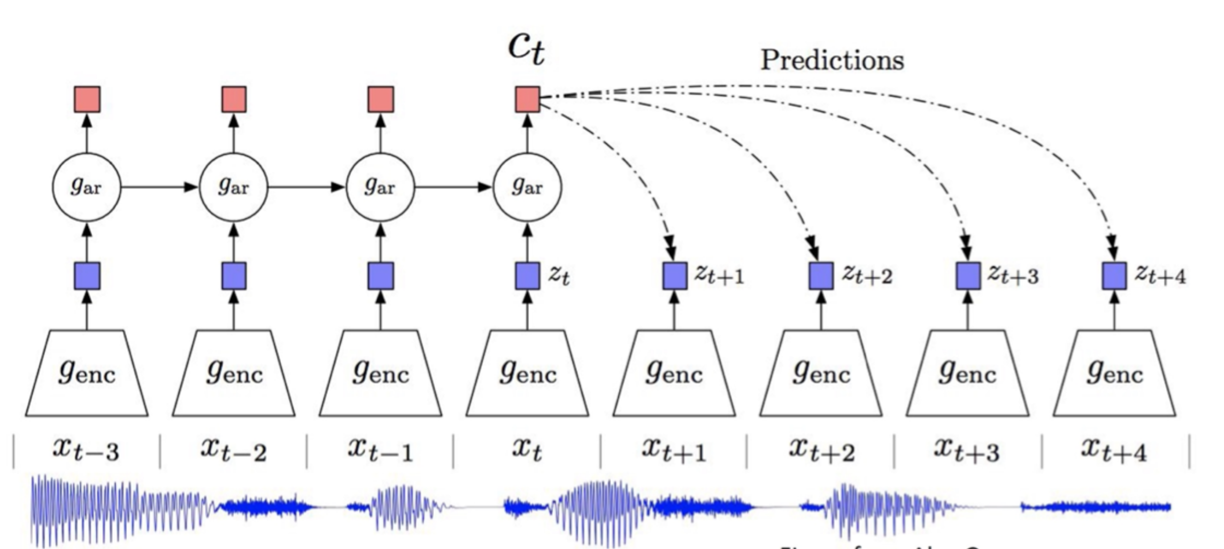


Figure from Alex Graves

$$f_k(x_{t+k}, c_t) = \exp\left(z_{t+k}^T W_k c_t\right)$$

$$\mathcal{L}_{\mathrm{N}} = -\mathop{\mathbb{E}}_{X}\left[\log \frac{f_k(x_{t+k}, c_t)}{\sum_{x_j \in X} f_k(x_j, c_t)}\right]$$

# Contrastive learning

**Contrastive Predictive Coding** (Van den Oord et al., ’18)

- CPC: Original proposed on audio data
- Use context to predict futures
    - Random negative samples required

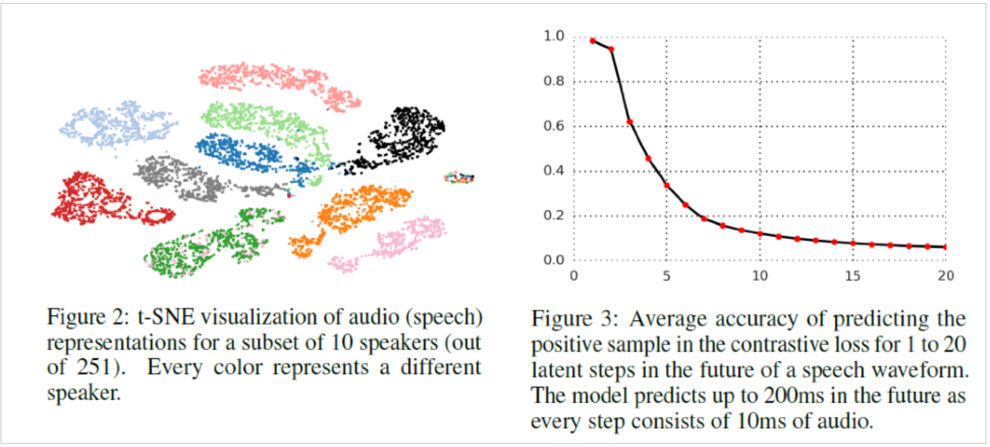
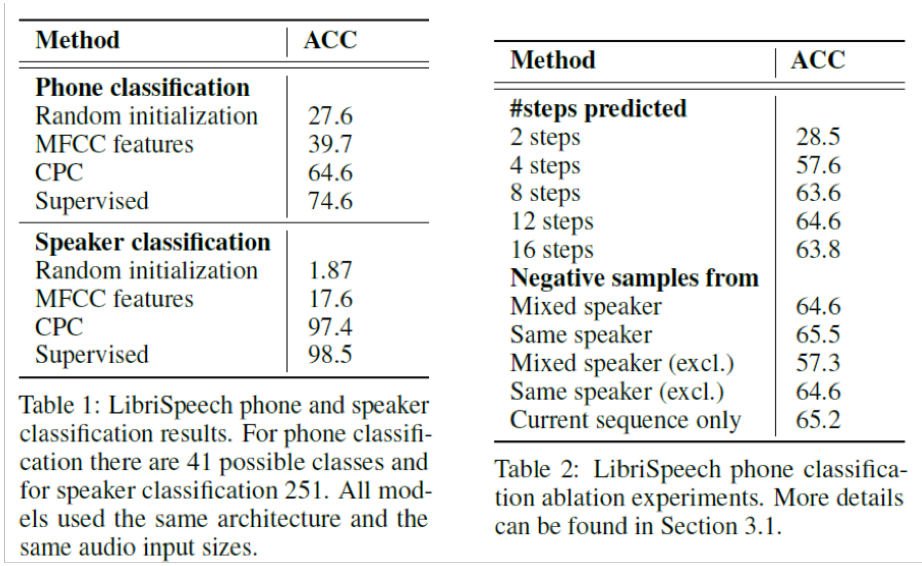


Figure 2: t-SNE visualization of audio (speech) representations for a subset of 10 speakers (out of 251). Every color represents a different speaker.

Figure 3: Average accuracy of predicting the positive sample in the contrastive loss for 1 to 20 latent steps in the future of a speech waveform. The model predicts up to 200ms in the future as every step consists of 10ms of audio.



| Method | ACC |
|---|---|
| **Phone classification** | |
| Random initialization | 27.6 |
| MFCC features | 39.7 |
| CPC | 64.6 |
| Supervised | 74.6 |
| **Speaker classification** | |
| Random initialization | 1.87 |
| MFCC features | 17.6 |
| CPC | 97.4 |
| Supervised | 98.5 |

Table 1: LibriSpeech phone and speaker classification results. For phone classification there are 41 possible classes and for speaker classification 251. All models used the same architecture and the same audio input sizes.

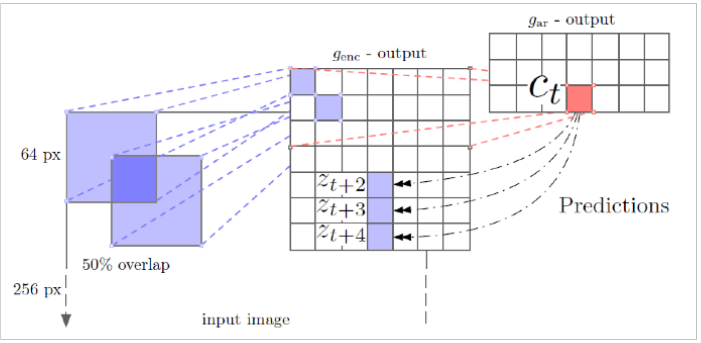
| Method | ACC |
|---|---|
| **#steps predicted** | |
| 2 steps | 28.5 |
| 4 steps | 57.6 |
| 8 steps | 63.6 |
| 12 steps | 64.6 |
| 16 steps | 63.8 |
| **Negative samples from** | |
| Mixed speaker | 64.6 |
| Same speaker | 65.5 |
| Mixed speaker (excl.) | 57.3 |
| Same speaker (excl.) | 64.6 |
| Current sequence only | 65.2 |

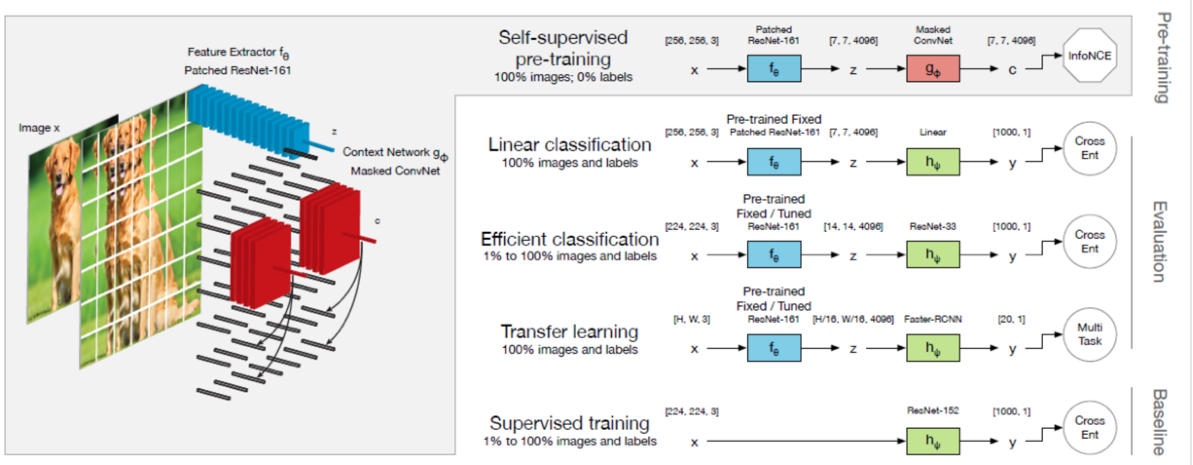
Table 2: LibriSpeech phone classification ablation experiments. More details can be found in Section 3.1.

# Contrastive learning

**Contrastive Predictive Coding** (Van den Oord et al., ’18)

- CPCv2: improved version of CPC on images with large scale training
  - PixelCNN, more prediction directions, path augmentation, layer normalization





# Contrastive learning

**Contrastive Predictive Coding** (Van den Oord et al., ’18)

- CPCv2: improved version of CPC on images with large scale training
  - PixelCNN, more prediction directions, path augmentation, layer normalization

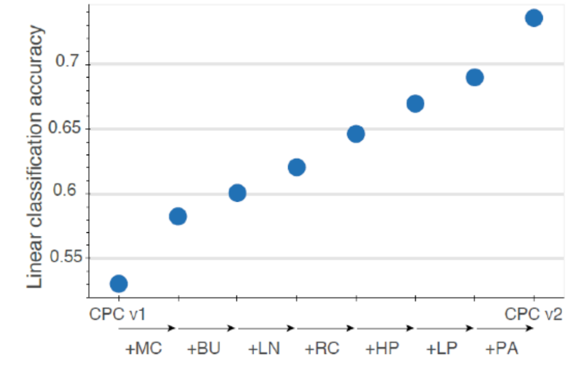
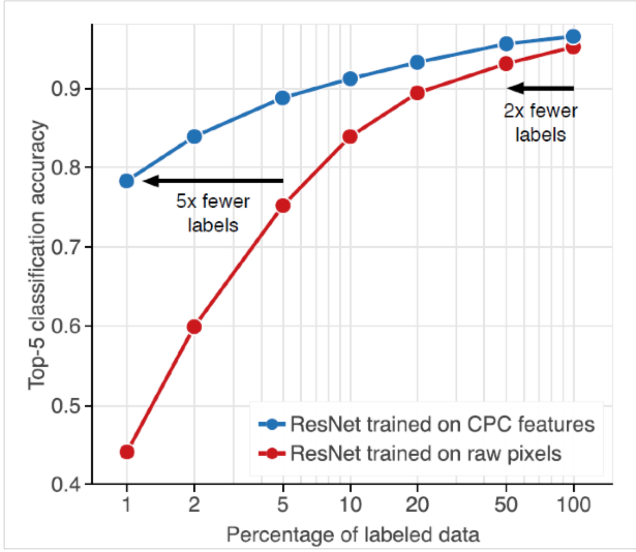


*Figure 3.* Linear classification performance of new variants of CPC, which incrementally add a series of modifications. MC: model capacity. BU: bottom-up spatial predictions. LN: layer normalization. RC: random color-dropping. HP: horizontal spatial predictions. LP: larger patches. PA: further patch-based augmentation. Note that these accuracies are evaluated on a custom validation set and are therefore not directly comparable to the results we report on the official validation set.

| METHOD | PARAMS (M) | TOP-1 | TOP-5 |
|---|---|---|---|
| *Methods using ResNet-50:* | | | |
| INSTANCE DISCR. [1] | 24 | 54.0 | - |
| LOCAL AGGR. [2] | 24 | 58.8 | - |
| MOCO [3] | 24 | 60.6 | - |
| PIRL [4] | 24 | 63.6 | - |
| CPC V2 - RESNET-50 | 24 | **63.8** | **85.3** |
| *Methods using different architectures:* | | | |
| MULTI-TASK [5] | 28 | - | 69.3 |
| ROTATION [6] | 86 | 55.4 | - |
| CPC V1 [7] | 28 | 48.7 | 73.6 |
| BIGBIGAN [8] | 86 | 61.3 | 81.9 |
| AMDIM [9] | 626 | 68.1 | - |
| CMC [10] | 188 | 68.4 | 88.2 |
| MOCO [2] | 375 | 68.6 | - |
| CPC V2 - RESNET-161 | 305 | **71.5** | **90.1** |



# Contrastive learning

**Contrastive Predictive Coding** (Van den Oord et al., ’18)

- MoCo: Momentum Contrastive Learning (He et al., ’20)

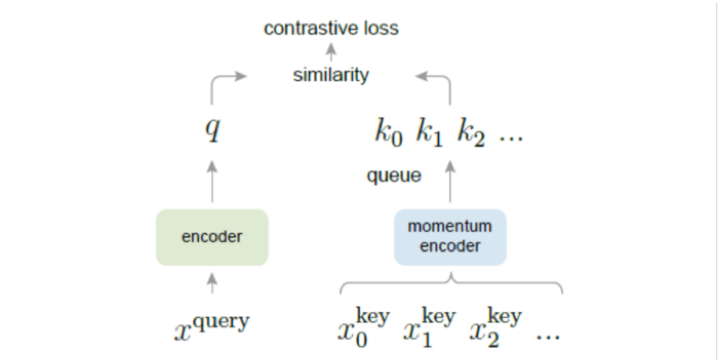
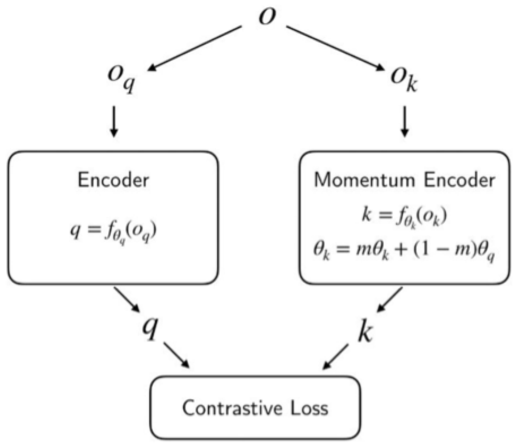


Figure 1. Momentum Contrast (MoCo) trains a visual representation encoder by matching an encoded query $q$ to a dictionary of encoded keys using a contrastive loss. The dictionary keys $\{k_0, k_1, k_2, \ldots\}$ are defined on-the-fly by a set of data samples. The dictionary is built as a queue, with the current mini-batch enqueued and the oldest mini-batch dequeued, decoupling it from the mini-batch size. The keys are encoded by a slowly progressing encoder, driven by a momentum update with the query encoder. This method enables a large and consistent dictionary for learning visual representations.

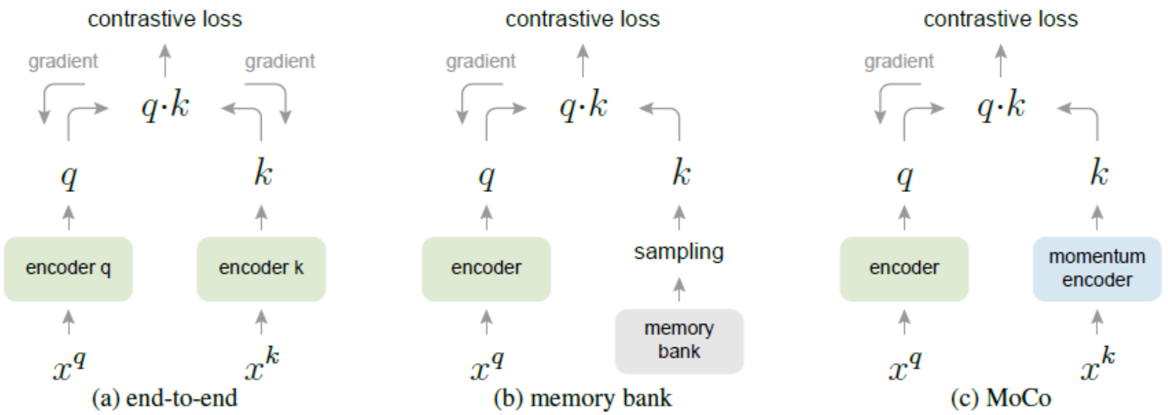


$$\mathcal{L}_q = -\log \frac{\exp(q \cdot k_+ / \tau)}{\sum_{i=0}^{K} \exp(q \cdot k_i / \tau)}$$

# Contrastive learning

**Contrastive Predictive Coding** (Van den Oord et al., ’18)

- MoCo: Momentum Contrastive Learning (He et al., ’20)
  - Why momentum encoder?
    - Enable large and consistent buffer of negative samples
    - Ensure the encoding in buffer moves slowly via momentum
      - Which further ensures the feature extractor updates smoothly



(a) end-to-end (b) memory bank (c) MoCo

Figure 2. **Conceptual comparison of three contrastive loss mechanisms** (empirical comparisons are in Figure 3 and Table 3). Here we illustrate one pair of query and key. The three mechanisms differ in how the keys are maintained and how the key encoder is updated. **(a)**: The encoders for computing the query and key representations are updated ***end-to-end*** by back-propagation (the two encoders can be different). **(b)**: The key representations are sampled from a ***memory bank*** [61]. **(c)**: ***MoCo*** encodes the new keys on-the-fly by a momentum-updated encoder, and maintains a queue (not illustrated in this figure) of keys.

# Contrastive learning

**Contrastive Predictive Coding** (Van den Oord et al., ’18)

- MoCo: Momentum Contrastive Learning (He et al., ’20)

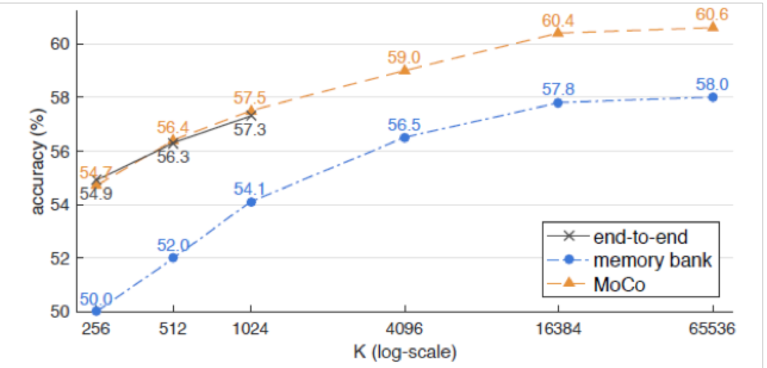
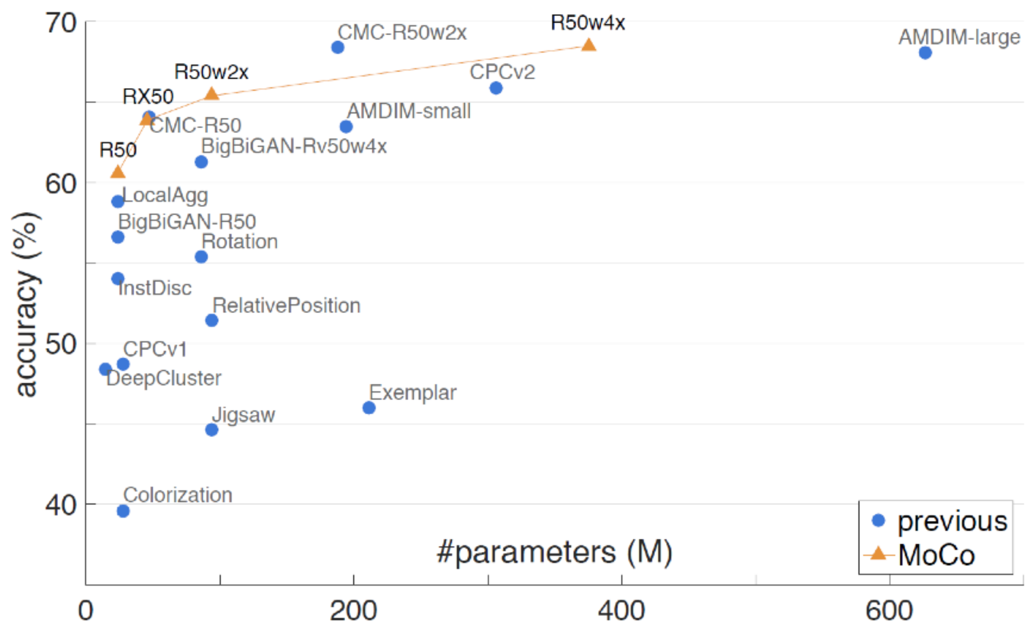


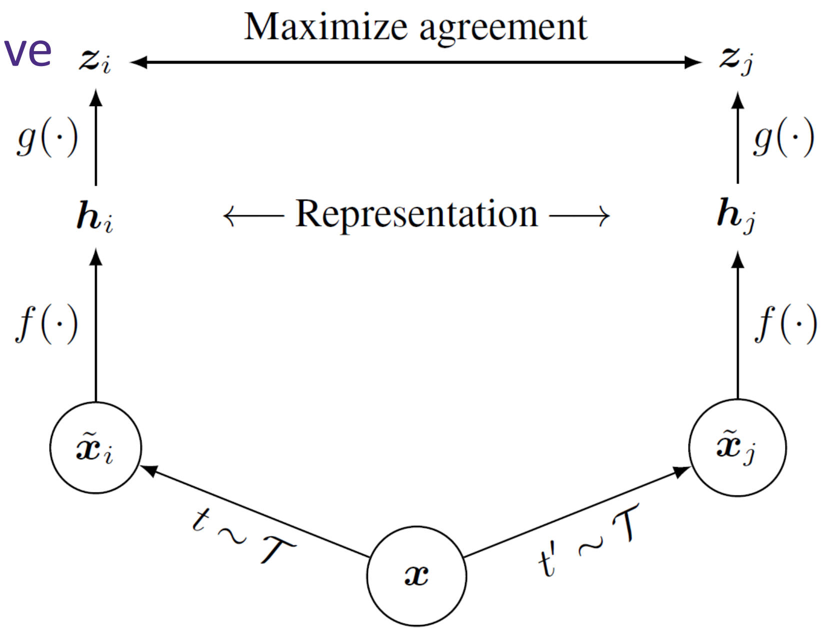
Figure 3. **Comparison of three contrastive loss mechanisms** under the ImageNet linear classification protocol. We adopt the same pretext task (Sec. 3.3) and only vary the contrastive loss mechanism (Figure 2). The number of negatives is $K$ in memory bank and MoCo, and is $K-1$ in end-to-end (offset by one because the positive key is in the same mini-batch). The network is ResNet-50.



# Contrastive learning

**Contrastive Predictive Coding** (Van den Oord et al., ’18)

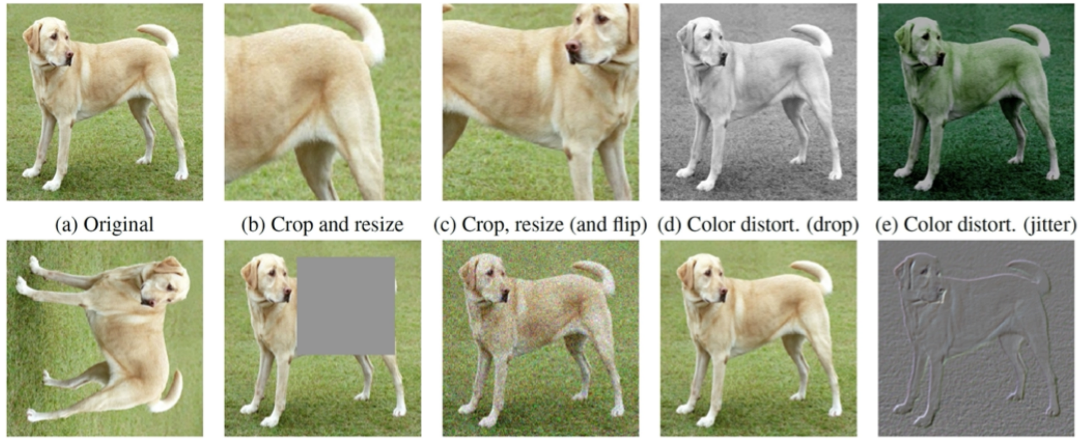
- SimCLR (Chen et al. ’20)
  - A simple framework for contrastive learning of visual representations
    - Predefine a set of transformations
    - For a data, sample two transformations
    - Maximum agreement on representations
  - No negative pairs explicitly
    - Non-paired data in the batch are negative



# Contrastive learning

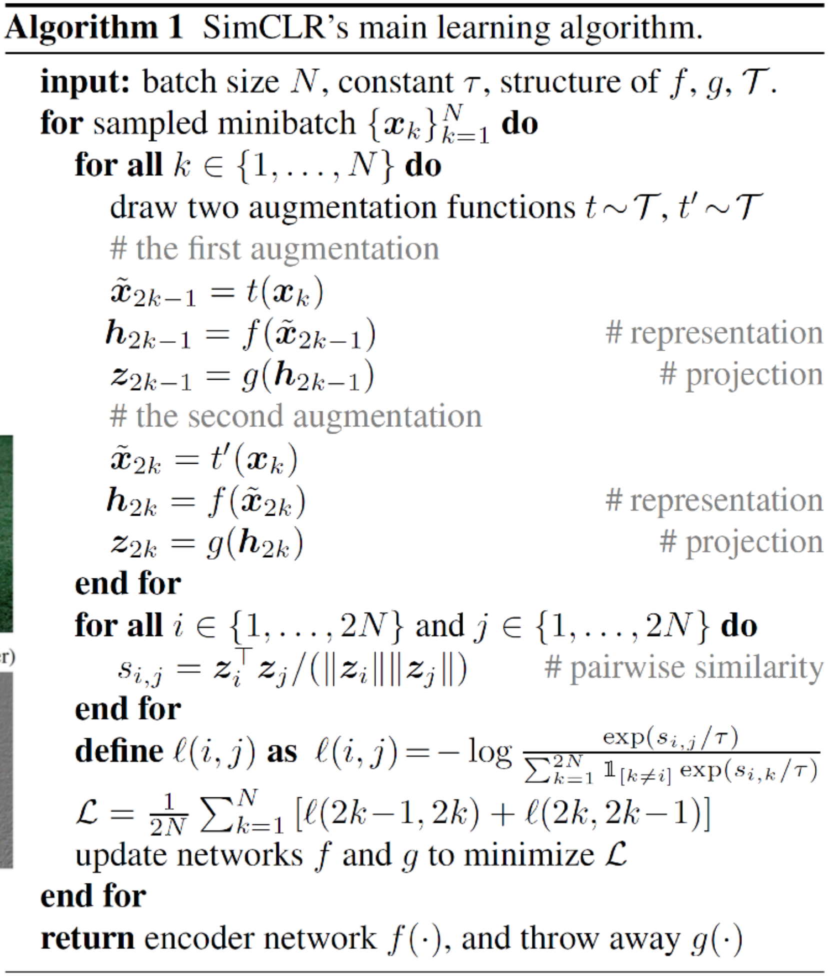
**Contrastive Predictive Coding** (Van den Oord et al., ’18)

- SimCLR (Chen et al. ’20)



(a) Original (b) Crop and resize (c) Crop, resize (and flip) (d) Color distort. (drop) (e) Color distort. (jitter)

(f) Rotate $\{90°, 180°, 270°\}$ (g) Cutout (h) Gaussian noise (i) Gaussian blur (j) Sobel filtering



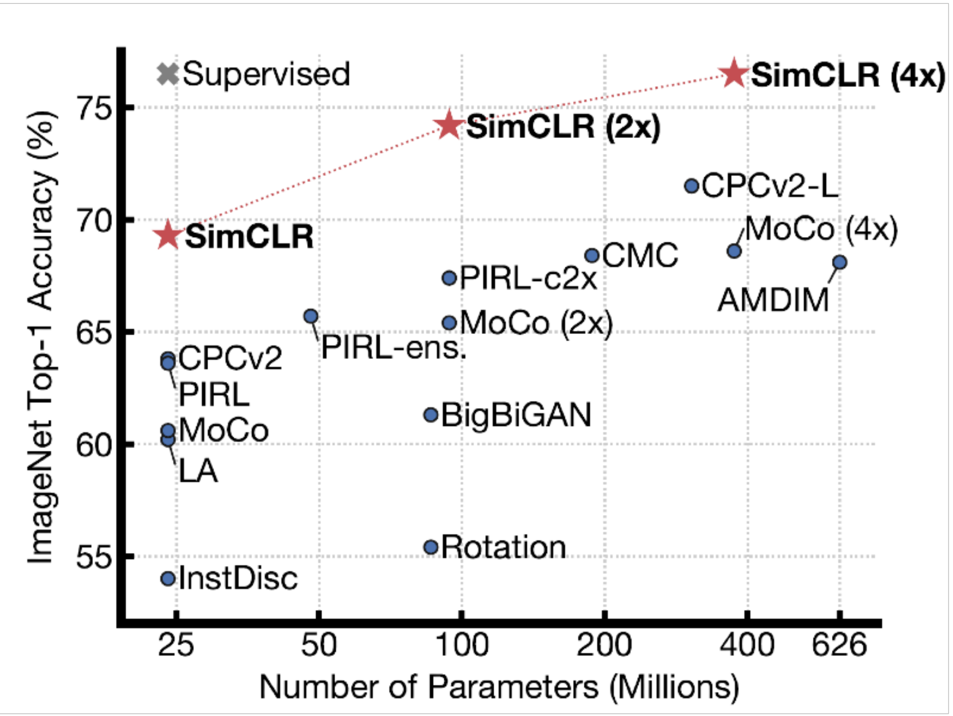
**Algorithm 1** SimCLR’s main learning algorithm.

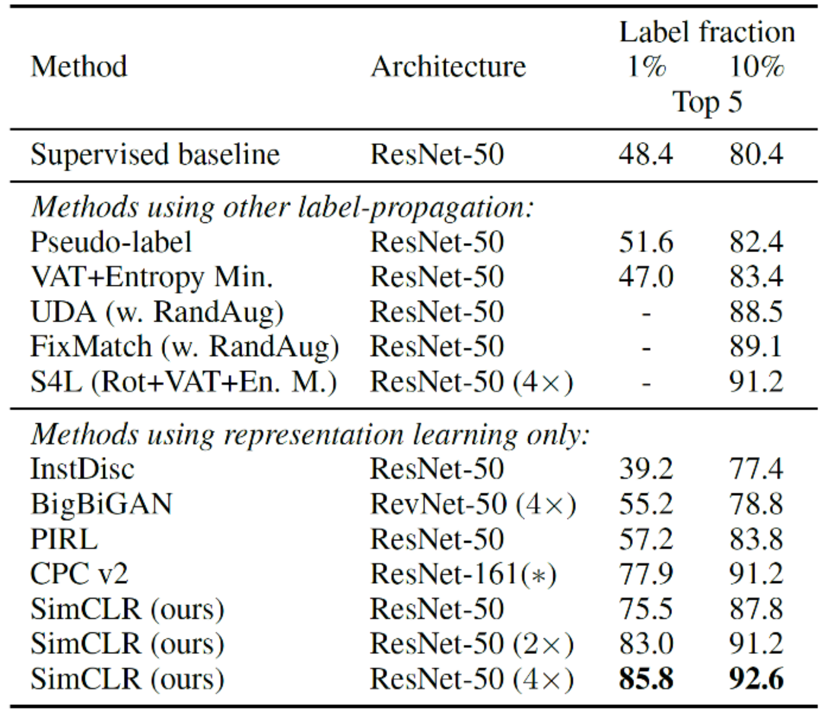
```
input: batch size $N$, constant $\tau$, structure of $f$, $g$, $\mathcal{T}$.
for sampled minibatch $\{\boldsymbol{x}_k\}_{k=1}^{N}$ do
  for all $k \in \{1, \ldots, N\}$ do
    draw two augmentation functions $t \sim \mathcal{T}$, $t' \sim \mathcal{T}$
    # the first augmentation
    $\tilde{\boldsymbol{x}}_{2k-1} = t(\boldsymbol{x}_k)$
    $\boldsymbol{h}_{2k-1} = f(\tilde{\boldsymbol{x}}_{2k-1})$                # representation
    $\boldsymbol{z}_{2k-1} = g(\boldsymbol{h}_{2k-1})$                        # projection
    # the second augmentation
    $\tilde{\boldsymbol{x}}_{2k} = t'(\boldsymbol{x}_k)$
    $\boldsymbol{h}_{2k} = f(\tilde{\boldsymbol{x}}_{2k})$                    # representation
    $\boldsymbol{z}_{2k} = g(\boldsymbol{h}_{2k})$                            # projection
  end for
  for all $i \in \{1, \ldots, 2N\}$ and $j \in \{1, \ldots, 2N\}$ do
    $s_{i,j} = \boldsymbol{z}_i^\top \boldsymbol{z}_j / (\|\boldsymbol{z}_i\| \|\boldsymbol{z}_j\|)$      # pairwise similarity
  end for
  define $\ell(i,j)$ as $\ell(i,j) = -\log \frac{\exp(s_{i,j}/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(s_{i,k}/\tau)}$
  $\mathcal{L} = \frac{1}{2N} \sum_{k=1}^{N} [\ell(2k-1, 2k) + \ell(2k, 2k-1)]$
  update networks $f$ and $g$ to minimize $\mathcal{L}$
end for
return encoder network $f(\cdot)$, and throw away $g(\cdot)$
```

# Contrastive learning

**Contrastive Predictive Coding** (Van den Oord et al., ’18)

- SimCLR (Chen et al. ’20)



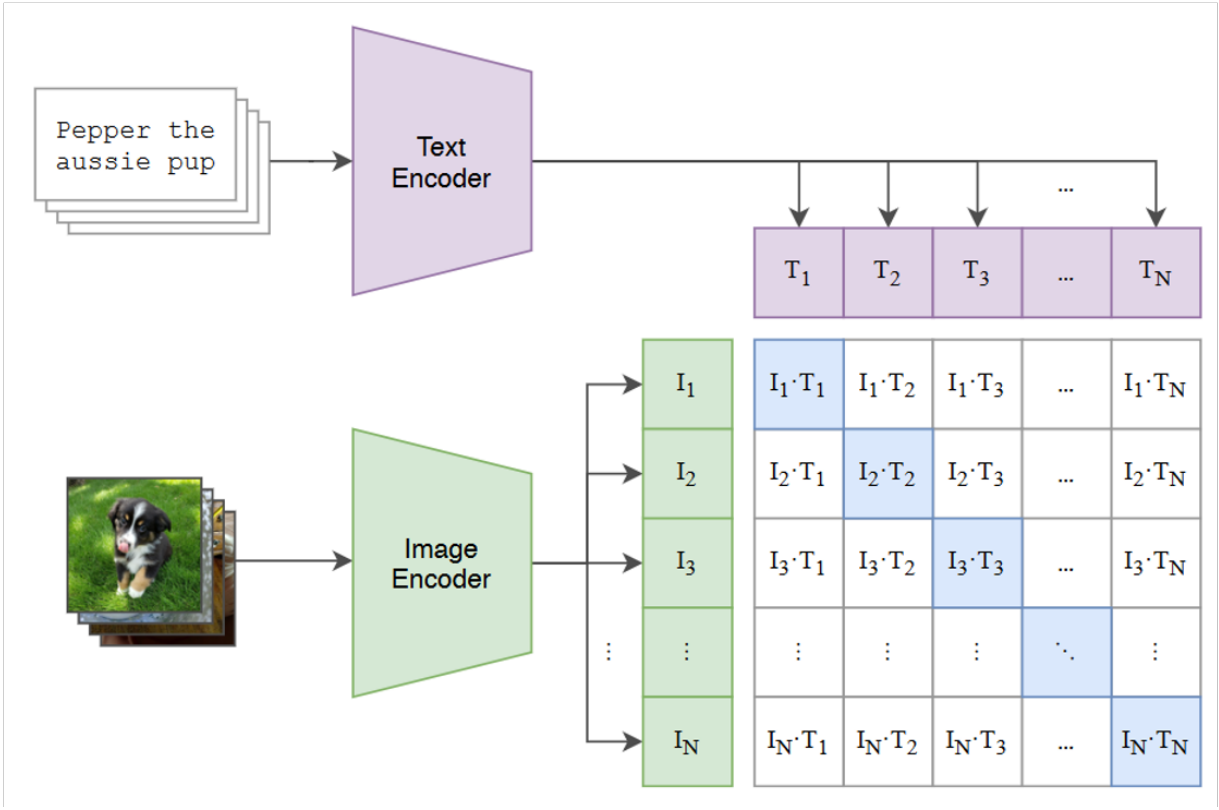


| Method | Architecture | Label fraction<br>1% | <br>10% |
|---|---|---|---|
| | | Top 5 | |
| Supervised baseline | ResNet-50 | 48.4 | 80.4 |
| *Methods using other label-propagation:* | | | |
| Pseudo-label | ResNet-50 | 51.6 | 82.4 |
| VAT+Entropy Min. | ResNet-50 | 47.0 | 83.4 |
| UDA (w. RandAug) | ResNet-50 | - | 88.5 |
| FixMatch (w. RandAug) | ResNet-50 | - | 89.1 |
| S4L (Rot+VAT+En. M.) | ResNet-50 (4×) | - | 91.2 |
| *Methods using representation learning only:* | | | |
| InstDisc | ResNet-50 | 39.2 | 77.4 |
| BigBiGAN | RevNet-50 (4×) | 55.2 | 78.8 |
| PIRL | ResNet-50 | 57.2 | 83.8 |
| CPC v2 | ResNet-161(∗) | 77.9 | 91.2 |
| SimCLR (ours) | ResNet-50 | 75.5 | 87.8 |
| SimCLR (ours) | ResNet-50 (2×) | 83.0 | 91.2 |
| SimCLR (ours) | ResNet-50 (4×) | **85.8** | **92.6** |

*Table 7.* ImageNet accuracy of models trained with few labels.

# Multimodal Contrastive Learning

**Contrastive Pretraining:**
Train image and text representation together



$$
\begin{array}{c|ccccc}
 & T_1 & T_2 & T_3 & \dots & T_N \\
\hline
I_1 & I_1 \cdot T_1 & I_1 \cdot T_2 & I_1 \cdot T_3 & \dots & I_1 \cdot T_N \\
I_2 & I_2 \cdot T_1 & I_2 \cdot T_2 & I_2 \cdot T_3 & \dots & I_2 \cdot T_N \\
I_3 & I_3 \cdot T_1 & I_3 \cdot T_2 & I_3 \cdot T_3 & \dots & I_3 \cdot T_N \\
\vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\
I_N & I_N \cdot T_1 & I_N \cdot T_2 & I_N \cdot T_3 & \dots & I_N \cdot T_N
\end{array}
$$

# Multimodal Contrastive Learning

**Loss function**

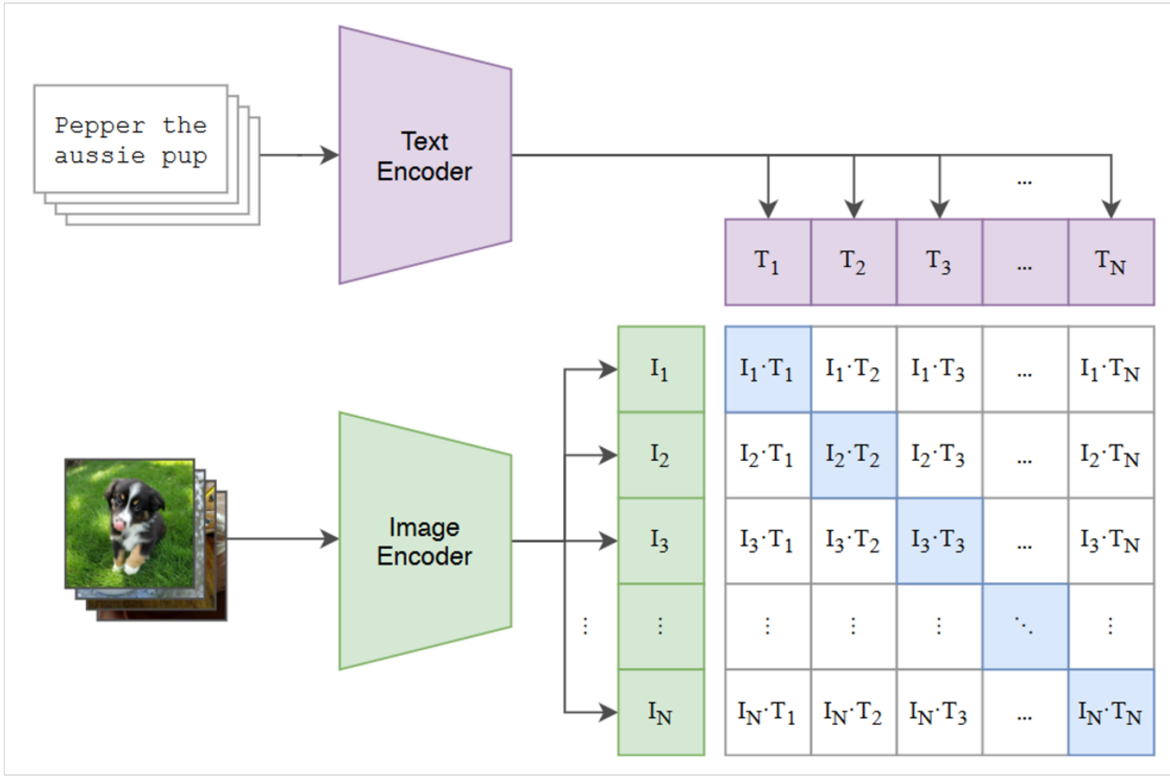
Let $q_{ij} := I_i^{\top} T_j$(normalized embeddings: $||I_i||_2 = ||T_j||_2 = 1$),

$$\text{loss} = \frac{\text{loss}_I + \text{loss}_T}{2}$$

where,

$$\text{loss}_I = -\sum_{i=1}^{N} \log \frac{\exp(q_{ii})}{\sum_j \exp(q_{ij})}$$

$$\text{loss}_T = -\sum_{j=1}^{N} \log \frac{\exp(q_{jj})}{\sum_i \exp(q_{ij})}$$

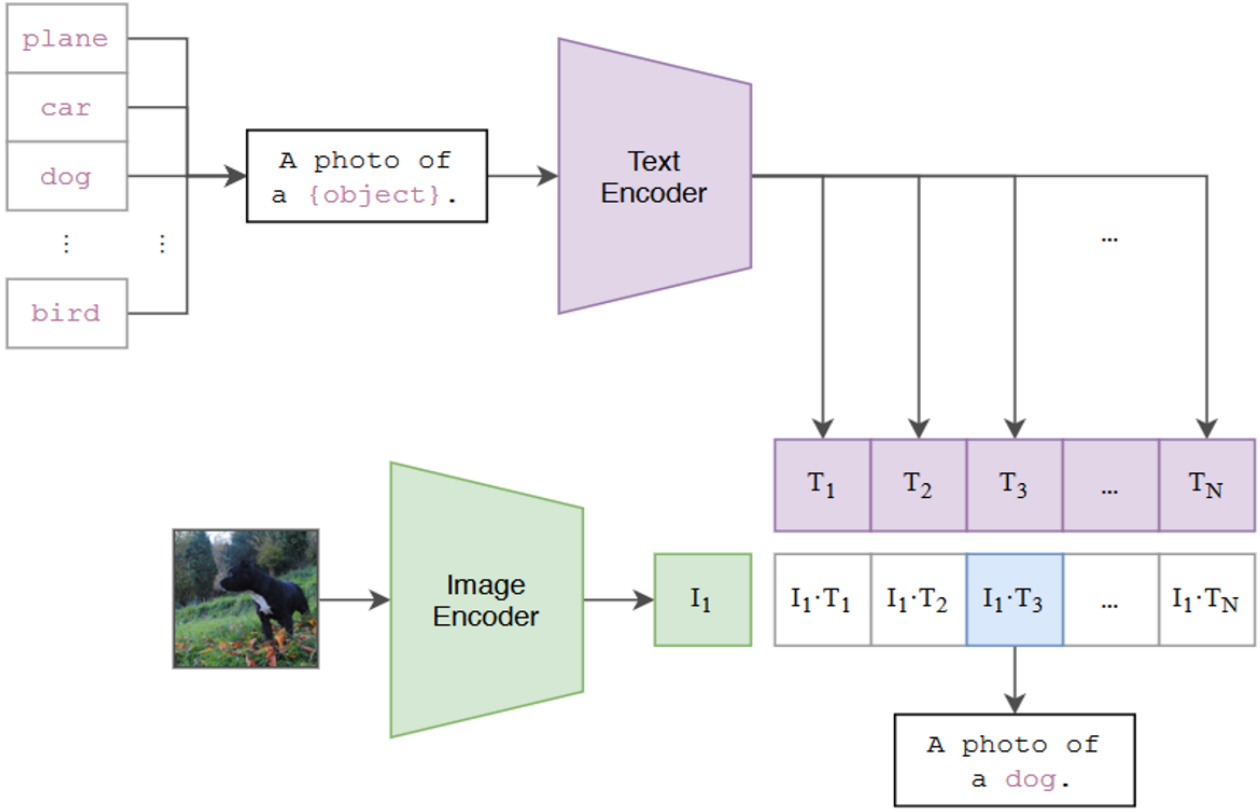


| | $T_1$ | $T_2$ | $T_3$ | ... | $T_N$ |
|---|---|---|---|---|---|
| $I_1$ | $I_1 \cdot T_1$ | $I_1 \cdot T_2$ | $I_1 \cdot T_3$ | ... | $I_1 \cdot T_N$ |
| $I_2$ | $I_2 \cdot T_1$ | $I_2 \cdot T_2$ | $I_2 \cdot T_3$ | ... | $I_2 \cdot T_N$ |
| $I_3$ | $I_3 \cdot T_1$ | $I_3 \cdot T_2$ | $I_3 \cdot T_3$ | ... | $I_3 \cdot T_N$ |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋱ | ⋮ |
| $I_N$ | $I_N \cdot T_1$ | $I_N \cdot T_2$ | $I_N \cdot T_3$ | ... | $I_N \cdot T_N$ |

# Multimodal Contrastive Learning

**Zero-Shot Classification:**

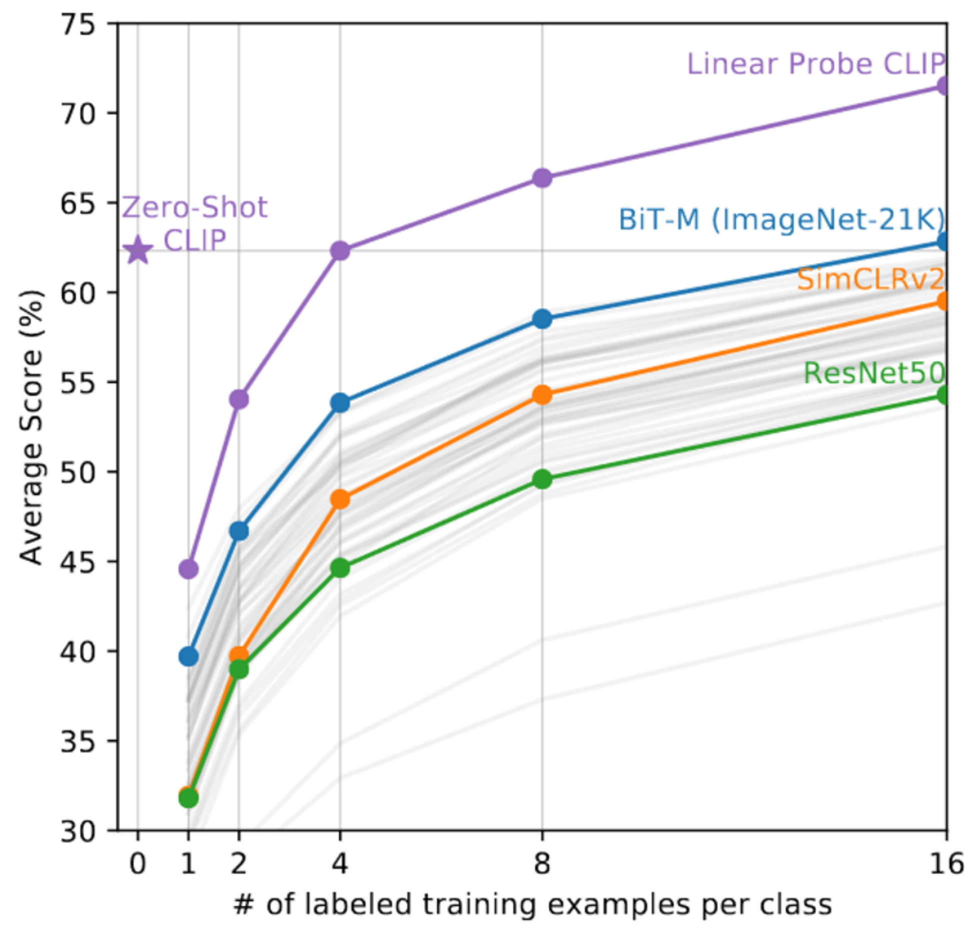
- Generate a prompt for each class



# Multimodal Contrastive Learning

## Results

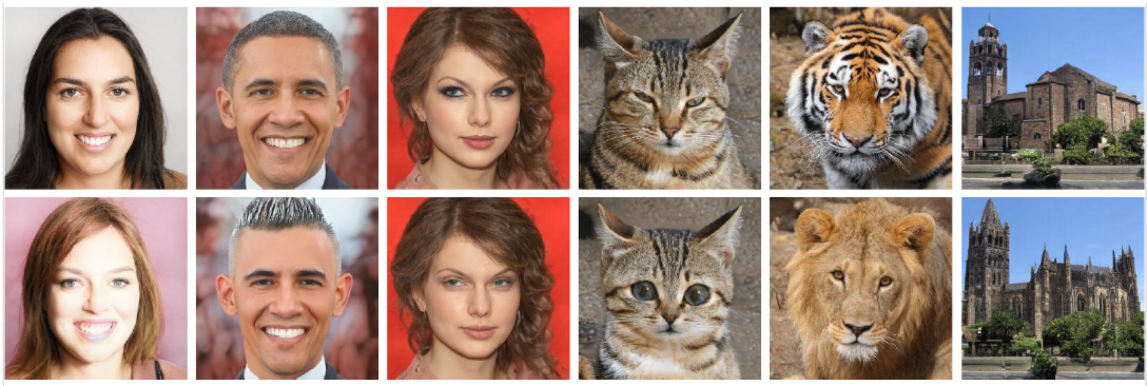
- Strong zero-shot and few-shot performance compared with other models.
- Zero-shot performance on **ImageNet**: CLIP ≈ fully supervised ResNet50!



# Applications of CLIP

Image Generation

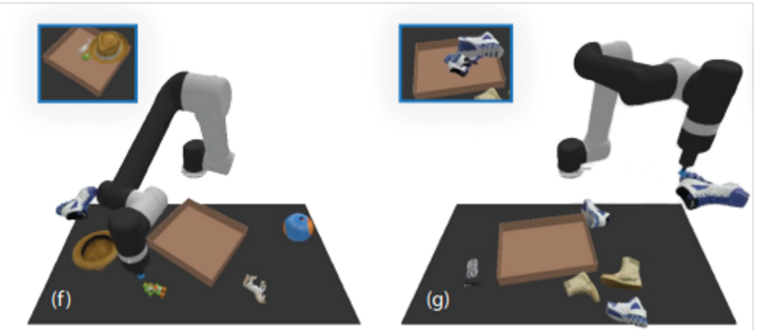
(StyleCLIP [Patashnik et al. 2021])



"Emma Stone" "Mohawk hairstyle" "Without makeup" "Cute cat" "Lion" "Gothic church"

Robotics

(CLIPort [Shridhar et al. 2021])



"pack the yoshi figure in the brown box"

"pack all the blue and black sneaker objects in the brown box"

...

# Problems about Training CLIP

Require large amount of ***carefully curated*** image-text pairs

**4 Billion** closed-source data used for OpenAI's CLIP

**Q: How to obtain lots of high-quality data?**

One choice: Web-curated data pairs + data filtering

# DataComp

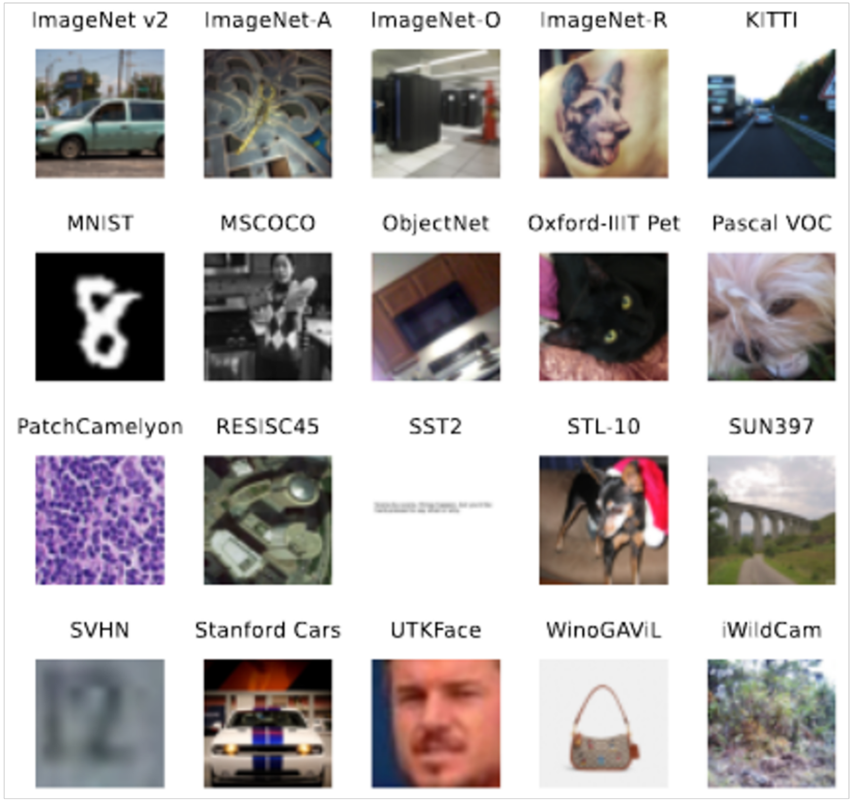
## A benchmark standardize the training configuration

Training Process:

- Filtering data from a pool of ***low-quality*** data pairs
- Train a CLIP model with a **fixed architecture** and **hyperparameters**
- Fix **total number of training data seen** (1 pass of 4B data = 4 passes of 1B data)

Evaluation:

- 38 Zero-shot downstream tasks



# Data Filtering

## Distribution-agnostic methods

### Image-based filtering

- Cluster the image embeddings (from a **pre-trained** CLIP model) of training data, and select the groups that contain at least one embedding from ImageNet-1k

### CLIP score filtering

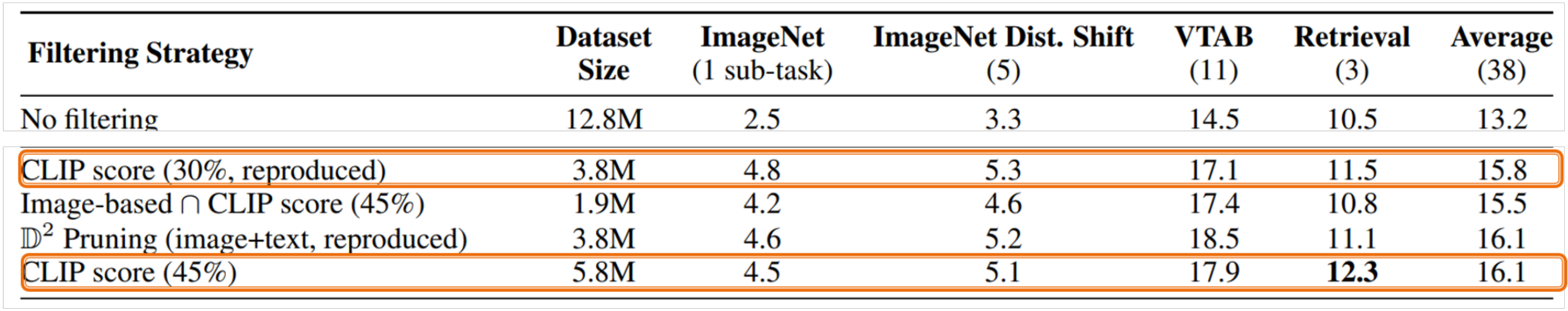
- Filter the data with low CLIP similarity assigned by a **pre-trained** CLIP model.

$$\text{CLIP score} = \bar{f}_{\text{image}}^{T} \bar{f}_{\text{text}}$$

# Data Filtering

**Setup:**

Total number of training sample seen = 12.8M



| Filtering Strategy | Dataset Size | ImageNet (1 sub-task) | ImageNet Dist. Shift (5) | VTAB (11) | Retrieval (3) | Average (38) |
|---|---|---|---|---|---|---|
| No filtering | 12.8M | 2.5 | 3.3 | 14.5 | 10.5 | 13.2 |
| CLIP score (30%, reproduced) | 3.8M | 4.8 | 5.3 | 17.1 | 11.5 | 15.8 |
| Image-based ∩ CLIP score (45%) | 1.9M | 4.2 | 4.6 | 17.4 | 10.8 | 15.5 |
| $\mathbb{D}^2$ Pruning (image+text, reproduced) | 3.8M | 4.6 | 5.2 | 18.5 | 11.1 | 16.1 |
| CLIP score (45%) | 5.8M | 4.5 | 5.1 | 17.9 | **12.3** | 16.1 |

Filtering significantly improves the performance!