

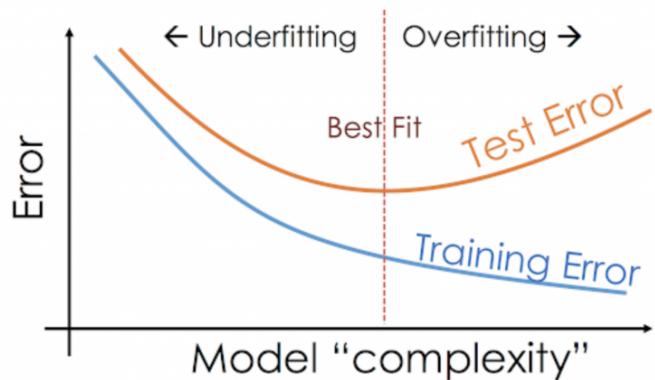


# Deep Learning 2

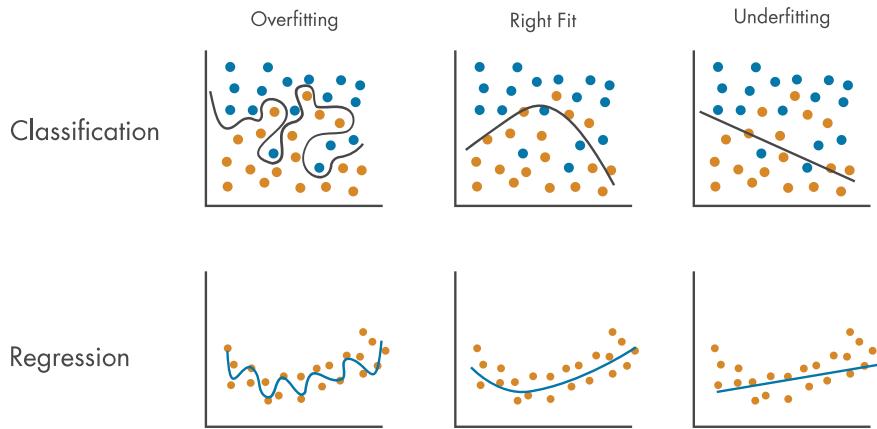
Use Unlabeled Data Effectively



# Overfitting, Generalization and Robustness



cite: Overfitting And Underfitting in Machine Learning



cite: What Is Overfitting?

- 當模型複雜度超過訓練資料集複雜度時，就容易發生 Overfitting
- 當訓練資料集複雜度超過模型複雜度時，就容易發生 Underfitting

# Overfitting, Generalization and Robustness

## 避免 Overfitting 的方法

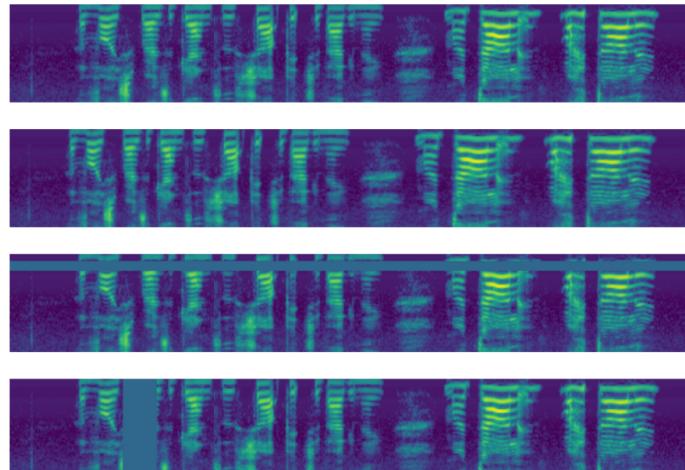
- 使用更多訓練資料
- 資料擴增 (Data Augmentation)
- Dropout
- L1/L2 Regularization
- 降低模型複雜度

## 避免 Underfitting 的方法

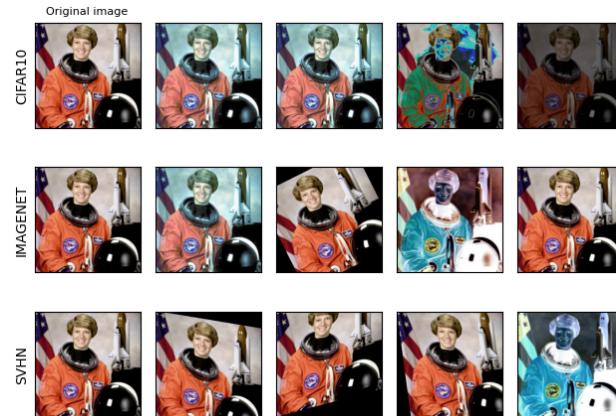
- 大力出奇蹟
- 叠更多參數能解決一切
- 錢是萬能的
- 用更強的硬體訓練更大的模型

# Overfitting, Generalization and Robustness

## Data Augmentation



cite: SpecAugment



cite: Pytorch: Illustration of transforms

## Test

- Replacing Words or Phrases with Their Synonyms
- Back Translation
- Text Generation
- Mixing-based Text Augmentation

# Overfitting, Generalization and Robustness

## Generalization

- 模型應用到其他資料分佈的能力

The classic approach towards the assessment of any machine learning model revolves around the evaluation of its generalizability i.e. its performance on unseen test scenarios.

## Robustness

- 模型對抗干擾的能力

Evaluating such models on an available non-overlapping test set is popular, yet significantly limited in its ability to explore the model's resilience to outliers and noisy data / labels (i.e. robustness).

cite: Generalizability vs. Robustness: Adversarial Examples for Medical Imaging, Robustness vs  
Generalization

# Garbage In, Garbage Out



- 資料稀缺

使用預訓練練（Pretrain）好的模型微調  
(fine-tune)

- 缺乏標記

使用 Self/Semi Supervised Learning

- 標記錯誤 Awesome-Noisy-Labels

- 分佈不平衡

Classification on imbalanced data

cite: 盡信資料，不如無資料

# Unlabeled Data

## Supervised

- 資料需要有人工標記
- 標記成本高昂、費時
- 無法輕易擴展資料集

## Semi-Supervised

訓練資料（同時使用）：

- 少量帶有人工標記的資料
- 大量的未標記資料

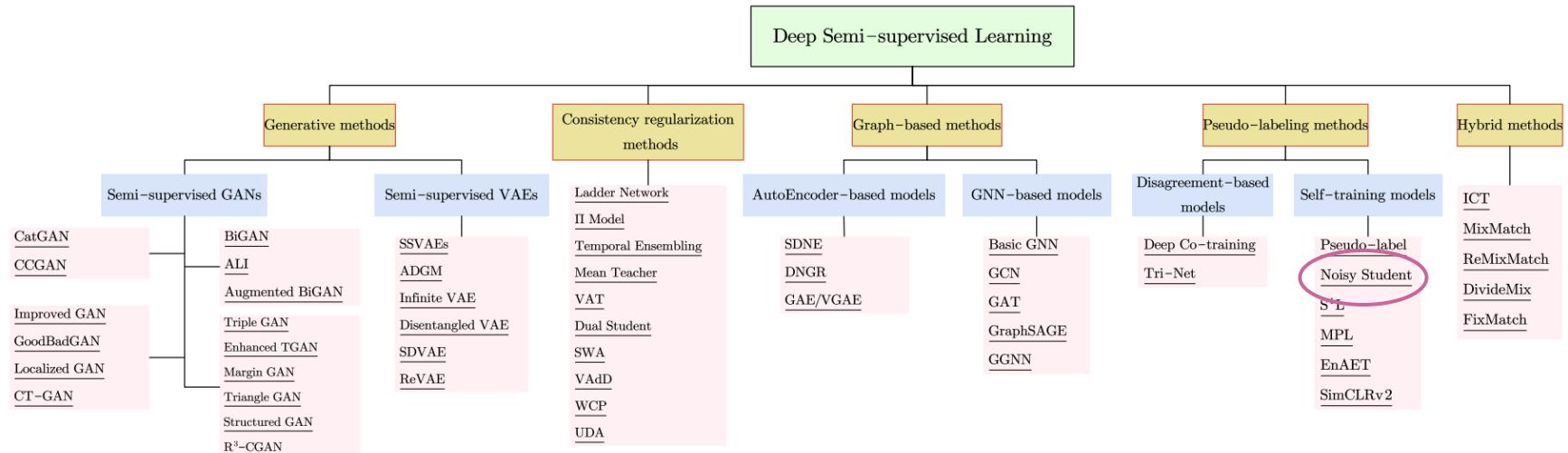
## Representation Learning

- 任務目標：抽取良好的資料特徵
- 可以是 Supervised or Unsupervised

## Self-Supervised

- 屬於 Unsupervised Learning 的一類
- 從大量的未標記資料中學習特徵
- 訓練好的模型應用在多個下游任務

# Semi-Supervised



cite: A Survey on Deep Semi-supervised Learning

# Semi-Supervised Noisy Student Training

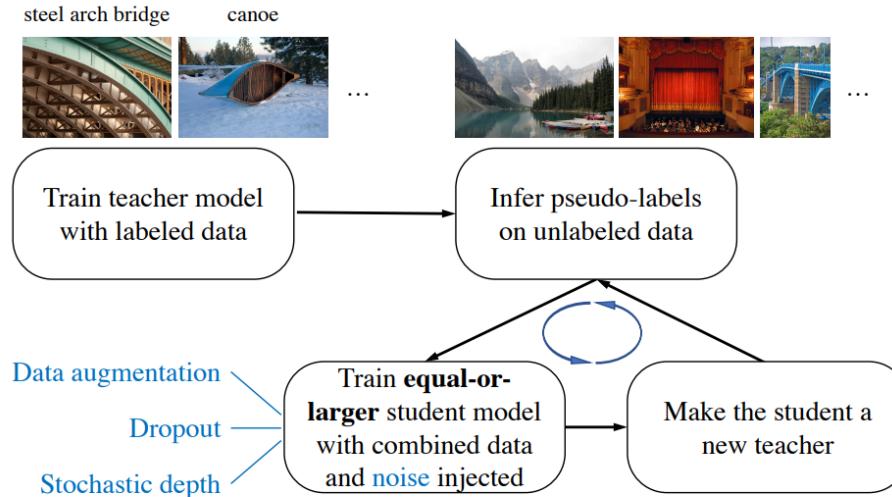


Figure 1: Illustration of the Noisy Student Training. (All shown images are from ImageNet.)

cite: Self-training with Noisy Student improves ImageNet classification

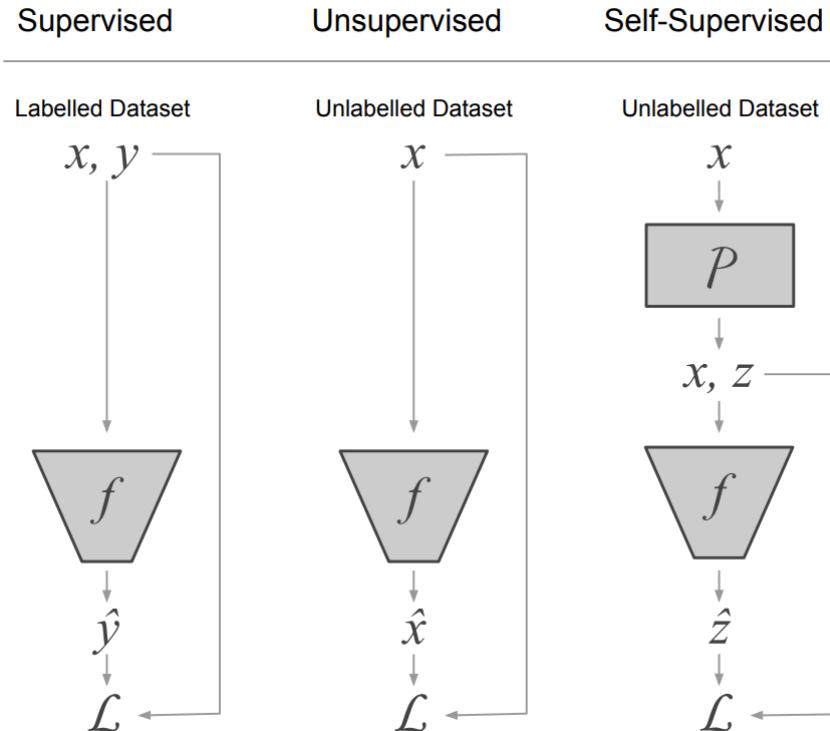
# Noisy Student Training

1. 在有人工標記的資料集  $\mathcal{D}$  上訓練模型 (Teacher)。
2. 在大量的未標記資料  $\mathcal{U}$  上使用 Teacher Model 推斷標籤得到  $\tilde{\mathcal{U}}$ 。
3. 使用通過資料增強的  $\mathcal{D} \cup \tilde{\mathcal{U}}$  訓練新的模型 (Noisy Student)。
4. 回到步驟 2，並使用 Noisy Student 取代 Teacher。

Model / Unlabeled Set Size	1.3M	130M
EfficientNet-B5	83.3%	84.0%
Noisy Student Training (B5)	<b>83.9%</b>	<b>85.1%</b>
student w/o Aug	83.6%	84.6%
student w/o Aug, SD, Dropout	83.2%	84.3%
teacher w. Aug, SD, Dropout	83.7%	84.4%

cite: Self-training with Noisy Student improves ImageNet classification

# Self-Supervised



cite: Self-Supervised Representation Learning:  
Introduction, Advances and Challenges

## Audio

- CPC
- Wav2Vec/2.0
- HuBERT

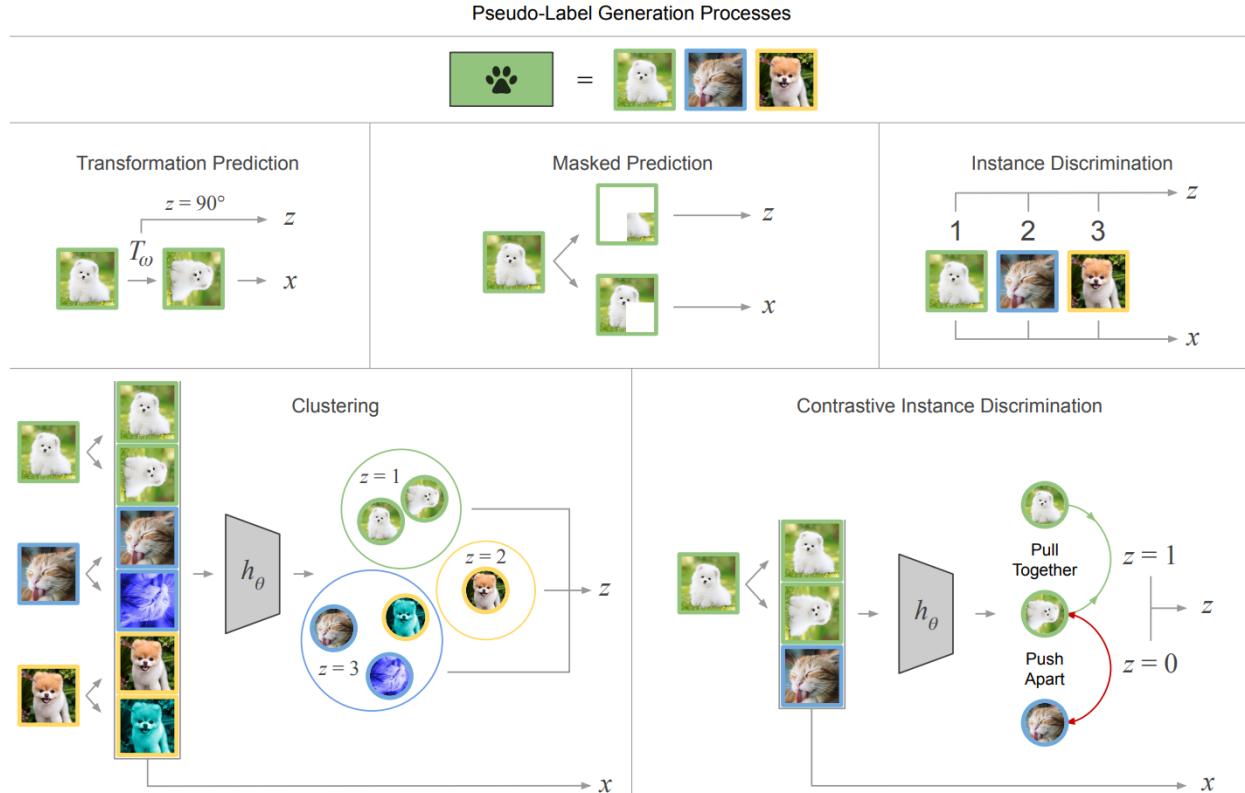
## Text

- BERT

## Image

- SimCLR
- BYOL
- DINoV1/v2

# Self-Supervised



cite: Self-Supervised Representation Learning: Introduction, Advances and Challenges

# Self-Supervised

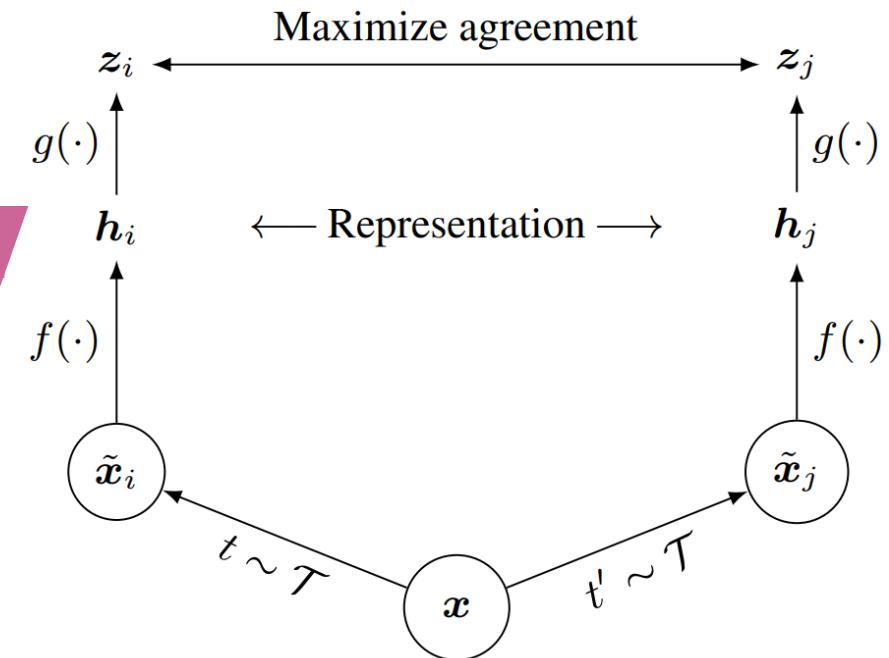
## SimCLR

- Contrastive Learning

$$l(i, j) = -\log \frac{\exp(s_{i,j}/\tau)}{\sum_{k=1}^{2N} \mathbf{1}_{k \neq i} \exp(s_{i,k}/\tau)}$$

$s_{i,j}$  is the cos similarity between  $z_i$  &  $z_j$ .

- 正樣本特徵越接近越好
- 負樣本特徵差越多越好
- $g(\cdot)$  是輔助骨幹網路  $f(\cdot)$  訓練的 projector，訓練完就會丟棄



cite: A Simple Framework for Contrastive Learning of Visual Representations

# Self-Supervised

## SimCLR

- 正樣本特徵**越接近越好**
- 負樣本特徵**差越多越好**
- $\text{MLP}=g(\cdot)$ ，輔助訓練的 projector
- $\text{CNN}=f(\cdot)$ ，骨幹網路

cite: [Advancing Self-Supervised and Semi-Supervised Learning with SimCLR](#)

# Self-Supervised Contrastive Learning

## Issues and Solutions

1. 需要大 Batch Size 才有足夠多的負樣本用來提昇性能

- 重複使用 Memory Bank 暫存的特徵當成正負樣本目標
- Momentum-updated Encoder 減少計算正負樣本目標消耗的記憶體

2. 需要從無標記的資料中建構正負樣本

- 設計無須使用負樣本的方法

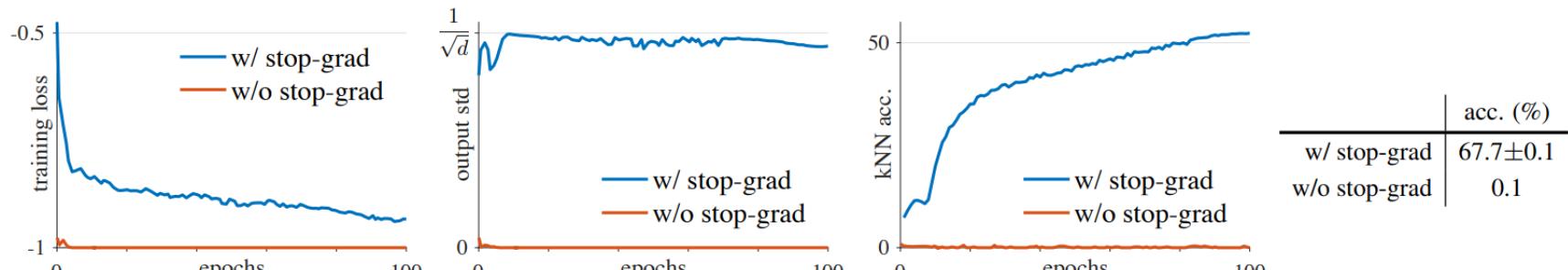
e.g. BYOL, SimSiam, DINOV1/v2

# Contrastive Learning Without Negative Sample

## Why Do We Need Negative Samples?

Contrastive Learning = 正樣本特徵越接近越好 + 負樣本特徵差越多越好

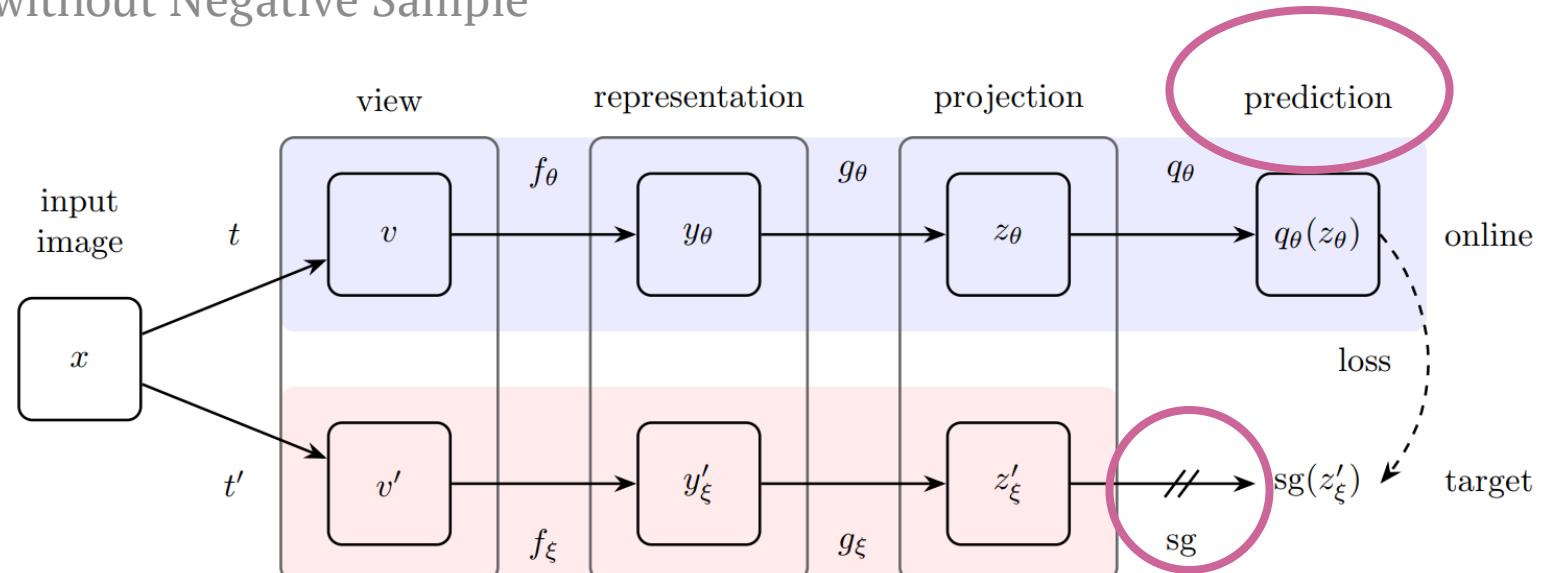
→ 只要模型輸出常數就能輕鬆達成，又稱為 Collapse (Trivial Solution)



cite: Exploring Simple Siamese Representation Learning

# Bootstrap Your Own Latent

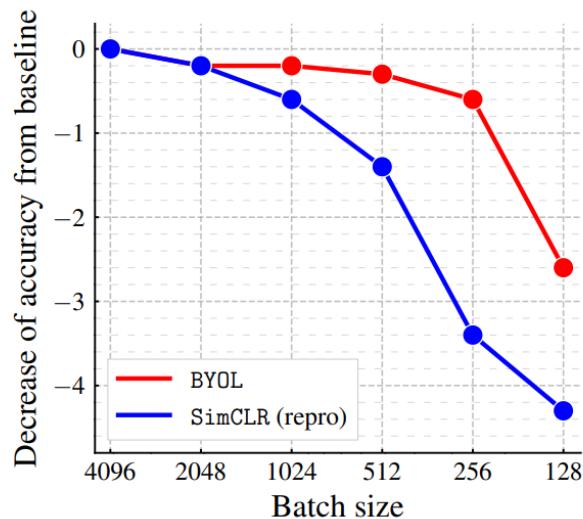
SSL without Negative Sample



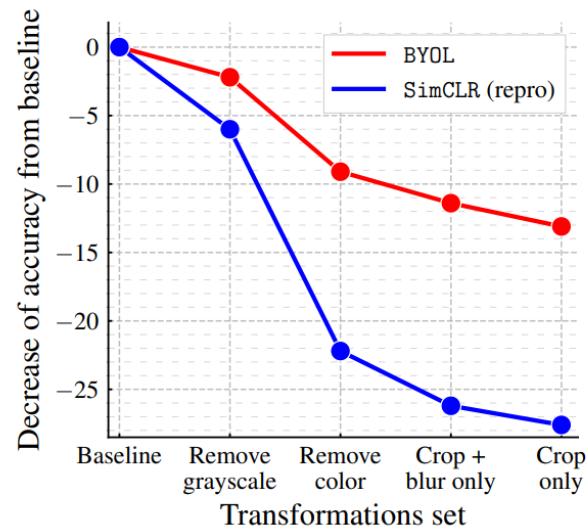
cite: [Bootstrap Your Own Latent A New Approach to Self-Supervised Learning](#)

# Bootstrap Your Own Latent

SSL without Negative Sample



(a) Impact of batch size



(b) Impact of progressively removing transformations

Figure 3: Decrease in top-1 accuracy (in % points) of BYOL and our own reproduction of SimCLR at 300 epochs, under linear evaluation on ImageNet.

cite: [Bootstrap Your Own Latent A New Approach to Self-Supervised Learning](#)

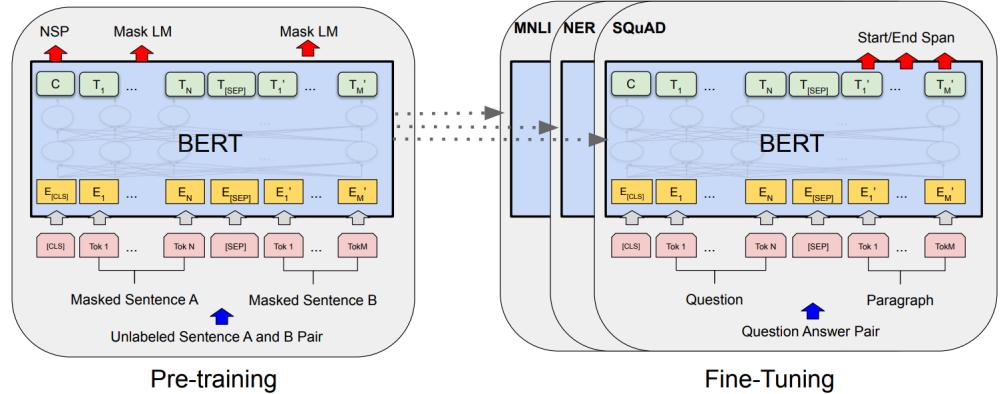
# SSL Without Negative Sample

method	batch size	negative pairs	momentum encoder	100 ep	200 ep	400 ep	800 ep
SimCLR (repro.+)	4096	✓		66.5	68.3	69.8	70.4
MoCo v2 (repro.+)	<b>256</b>	✓	✓	67.4	69.9	71.0	72.2
BYOL (repro.)	4096		✓	66.5	<b>70.6</b>	<b>73.2</b>	<b>74.3</b>
SwAV (repro.+)	4096			66.5	69.1	70.7	71.8
<b>SimSiam</b>	<b>256</b>			<b>68.1</b>	70.0	70.8	71.3

cite: Exploring Simple Siamese Representation Learning

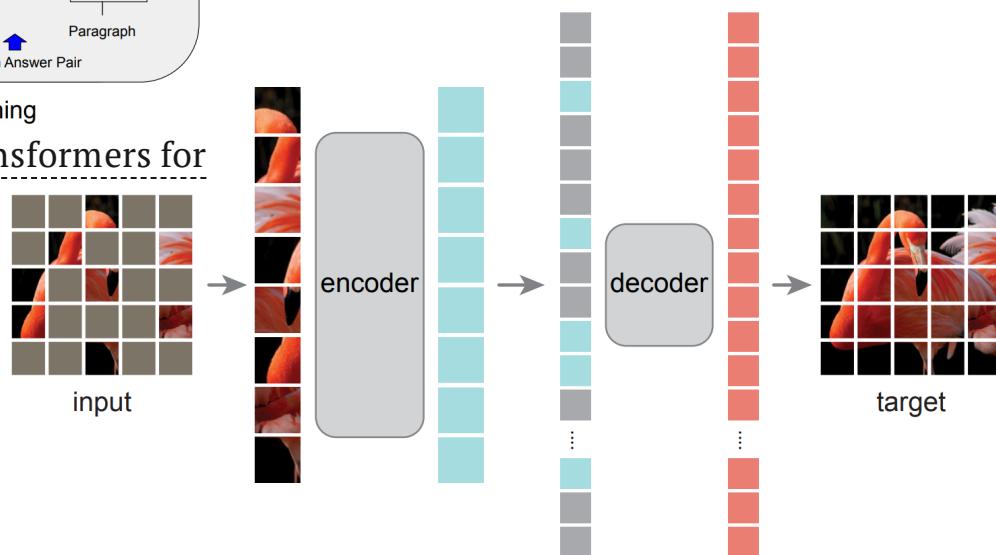
- 實作簡單
- 性能優異
- 無需定義負樣本
- 若超參數沒設好，有發生 collapse 的風險

# Masked AutoEncoder



cite: BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding

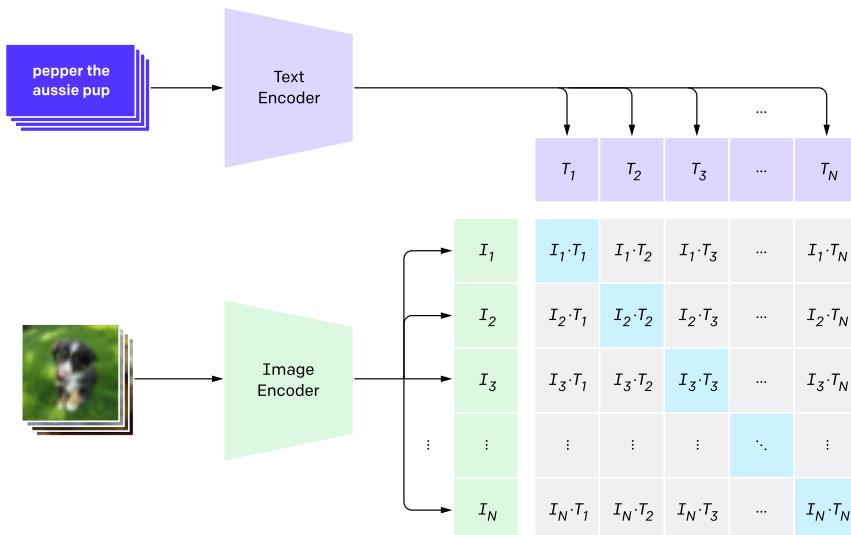
- 穩定、容易訓練
- 不會 collapse
- 適合 Transformer 學習全域特徵



cite: Masked Autoencoders Are Scalable Vision Learners 20 / 23

# Representation Learning

## 1. Contrastive pre-training



cite: Learning Transferable Visual Models From  
Natural Language Supervision

Text & Text

- Sentence-BERT

Text & Image

- CLIP

- CoCa

Multimodal

- Data2Vec

- ImageBind

# Survey

## Self-Supervised

- Self-Supervised Representation Learning
- Contrastive Representation Learning
- Awesome Self-Supervised Learning
- 自監督式學習 Self-Supervised Learning for Computer Vision 之概述
- A Survey on Contrastive Self-supervised Learning, 2020
- Self-Supervised Representation Learning: Introduction, Advances and Challenges, 2021
- Self-Supervised Learning for Videos: A Survey, 2022
- Survey on Self-Supervised Learning: Auxiliary Pretext Tasks and Contrastive Learning Methods in Imaging, 2022
- Self-Supervised Speech Representation Learning: A Review, 2022
- A Survey of Self-Supervised Learning from Multiple Perspectives: Algorithms, Theory, Applications and Future Trends, 2023

# Survey

## Semi-Supervised

- An Overview of Deep Semi-Supervised Learning, 2020
- A Survey on Deep Semi-supervised Learning, 2021