

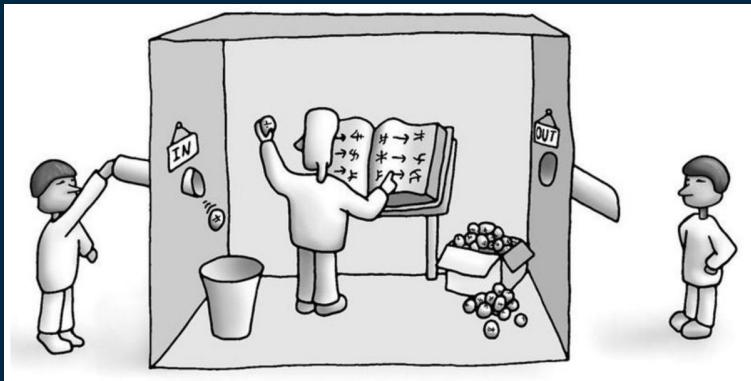
# SELF SUPERVISED LEARNING

SimCLR & NLP

By  
Milis Sahar

## The Chinese Room Argument

First published Fri Mar 19, 2004;  
substantive revision Thu Feb 20, 2020



“It has become one of the best-known arguments in recent philosophy.”



“Self-supervised learning is the dark matter of intelligence”

Yan LaCun, FAIR

(DM is 85% of the matter in the universe)

Turn left!



# ABOUT ME



## SAHAR MILLIS

NLP DATA SCIENTIST @VIMEO

Student & T.A, MSc Data Science @RU

<https://medium.com/@sahar.millis>



# ON THE NEXT 30 MINUTES...



01

SLL

Timeline, Data, Methods



02

SimCLR

Article, Training, Findings



03

SLL & NLP

LMs, SimCSE

# SSL

Self-Supervised Learning is an ML method.  
It learns from unlabeled sample data.  
It's an intermediate form between  
supervised and unsupervised learning.

Self-supervised learning has produced  
promising results in recent years.

The primary appeal of SSL is that training  
can occur with data of lower quality.

Self-supervised learning more closely  
imitates the way humans learn.



# SSL TIMELINE (models)

Unsupervised Translation

Meta



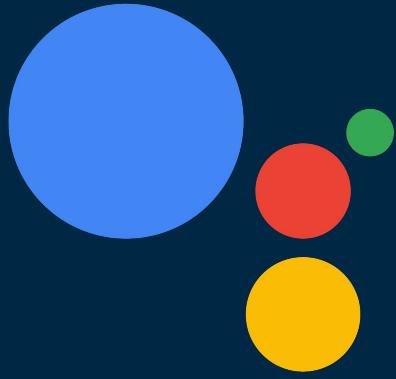
RoBERTa  
Wave2Vec

ViLBERT, RIO  
SimSearch

2021  
Textless NLP  
PyTorchVideo  
HuBERT

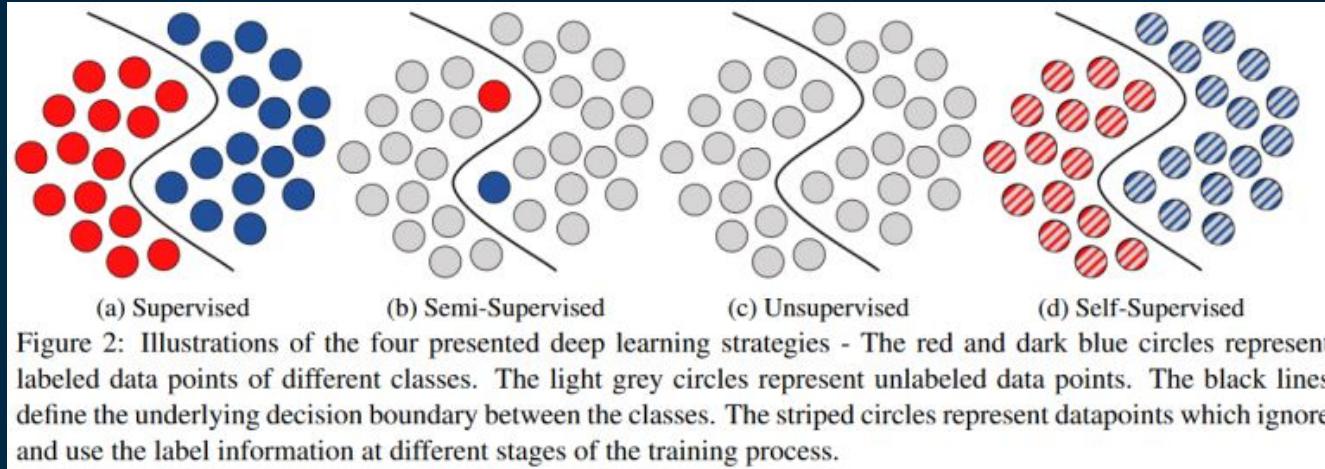
2018

2020



You're using SSL every day...

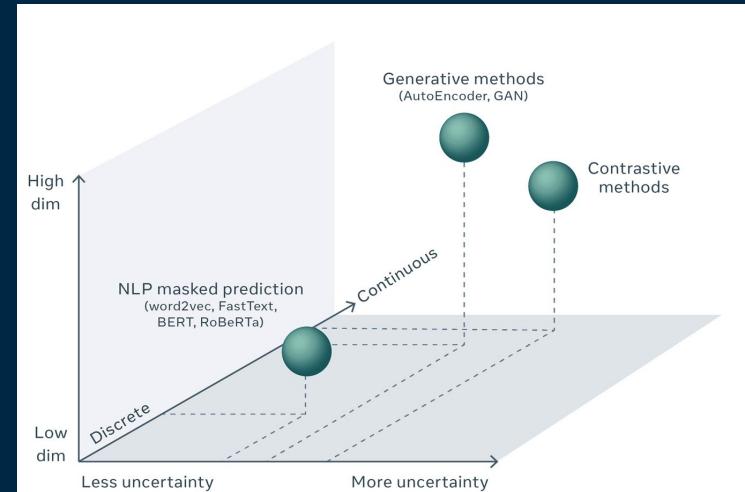
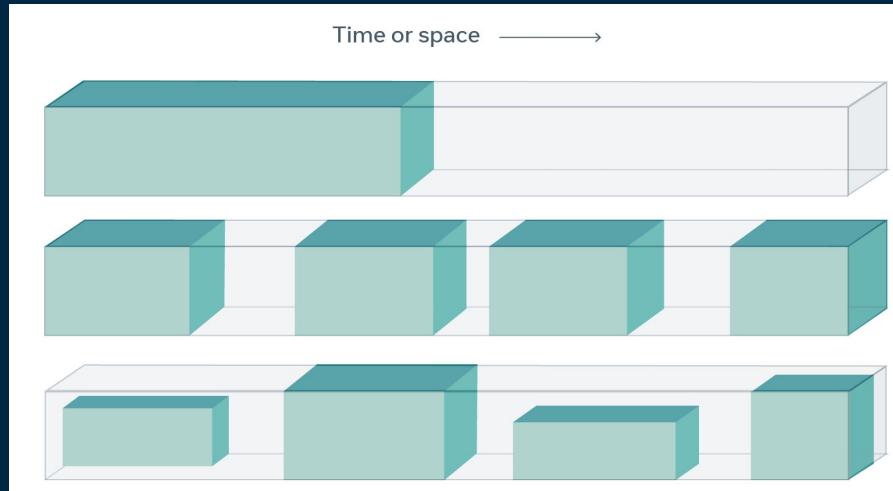
# WHERE IS SSL?



Semi-, Self- and Unsupervised Learning in Image Classification (May, 2021)

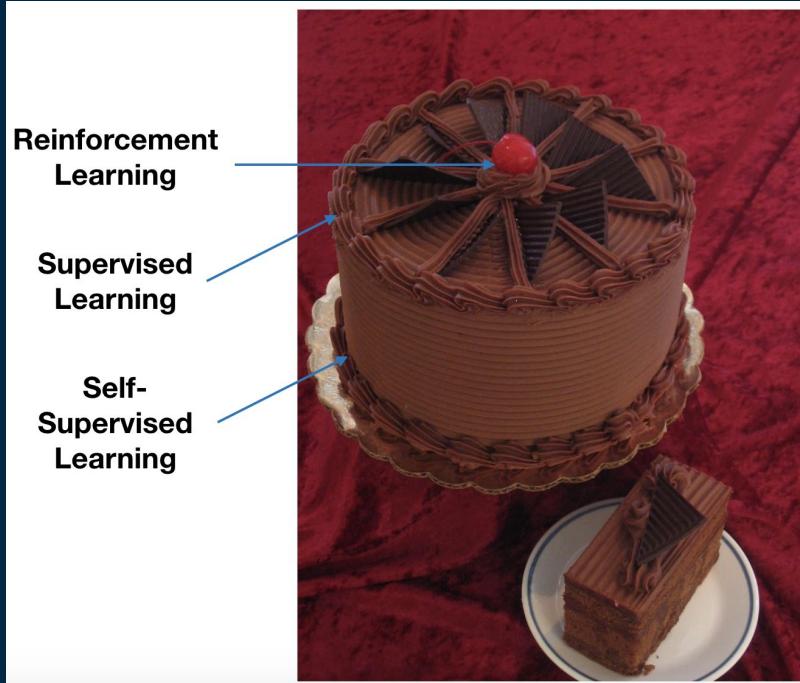
# DATA

Self-supervised learning obtains supervisory signals from the data itself, often leveraging the underlying structure in the data.



# PREDICTIVE LEARNING

“cake analogy”  
by Prof. Yan LaCun  
At the NIPS 2016 conference  
Referring to Predictive Learning

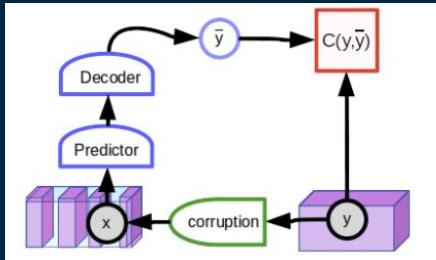


# SSL TECHNIQUES



constructing pairs of  $x$  and  $y$  that are not compatible

## Contrastive

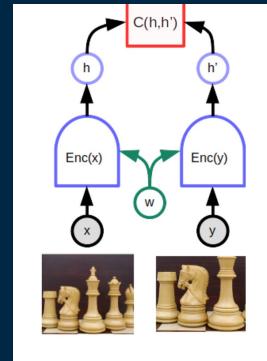


measures distance between vectors produced by identical networks

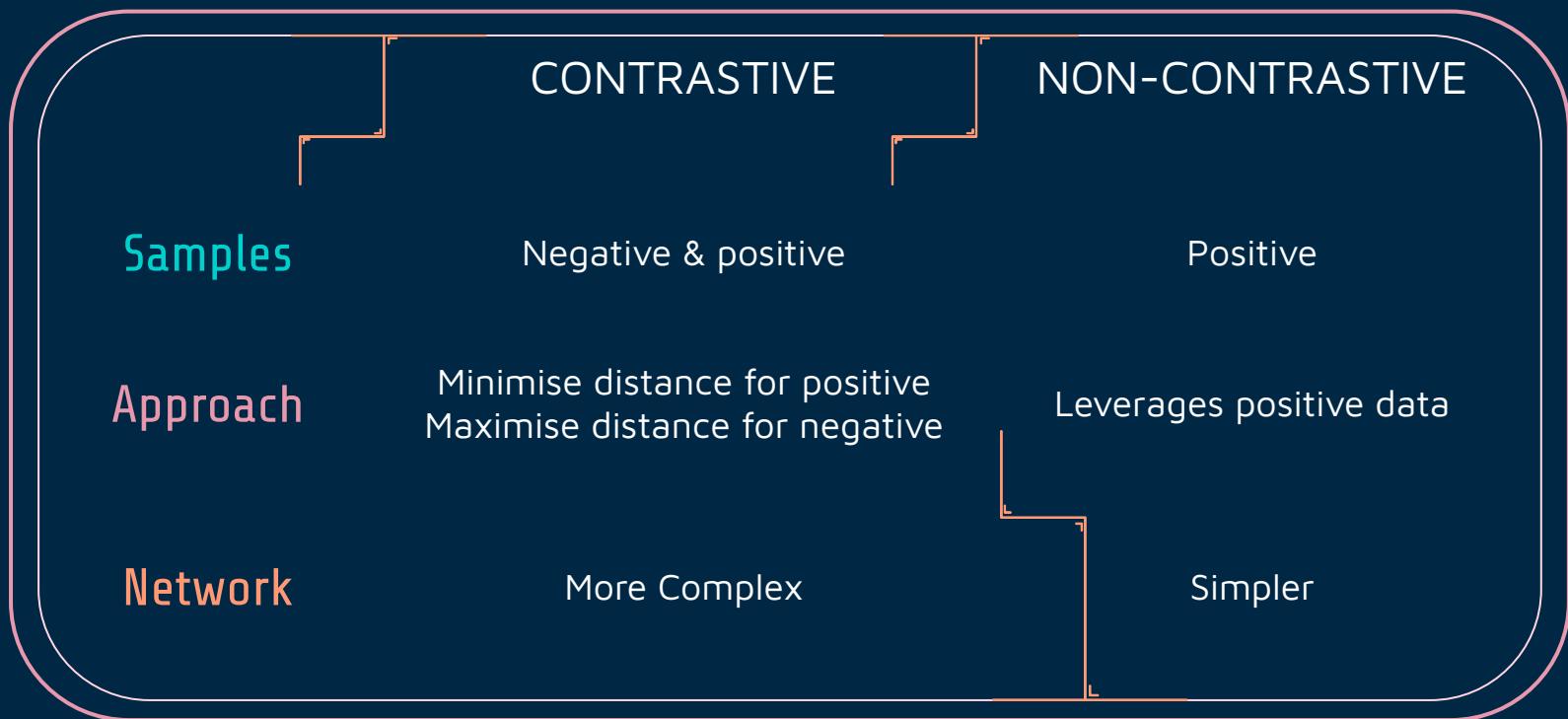
## Siamese networks

## Non-contrastive

Deeper-Cluster, ClusterFit,  
MoCo-v2, SwAV, SimSiam



# Contrastive vs Non-Contrastive



# SSL TASKS



ervation  $x$  and a proposed prediction  $y$ .

## Joint embedding



Classify unstructured text into names, organizations, locations, dates, quantities, etc.

## Named Entity Recognition



Segmentation, Categories, Semantic Analysis, etc.

## Non-contrastive



constructing pairs of  $x$  and  $y$  that are not compatible,

## Contrastive



Generate Text2Text, Text2Code, Image2Text, etc.

## Siamese networks



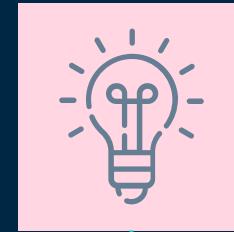
Semantic Similarity, Relation Predictions, etc.

## Text Pair Matching

# SimCLR

Jul 2020

A Simple Framework for Contrastive Learning of Visual Representations



# SimCLR Article

Almost 5K cited

Using Contrastive Loss as SSL

Key findings: Augmentation, Projection, Scale

## A simple framework for contrastive learning of visual representations

[T Chen](#), [S Kornblith](#), [M Norouzi](#)... - ... conference on machine ..., 2020 - proceedings.mlrv.press

This paper presents SimCLR: a simple framework for contrastive learning of visual representations. We simplify recently proposed contrastive self-supervised learning algorithms without requiring specialized architectures or a memory bank. In order to understand what enables the contrastive prediction tasks to learn useful representations, we systematically study the major components of our framework. We show that (1) composition of data augmentations plays a critical role in defining effective predictive tasks,(2) ...

☆ Save

CIT

Cited by 4718 Related articles All 19 versions

# Contrastive Loss

Key Ideas:

Same Class -> Similar Embeddings

Different Class -> Dissimilar Embeddings

(Challenge: How do you sample?)

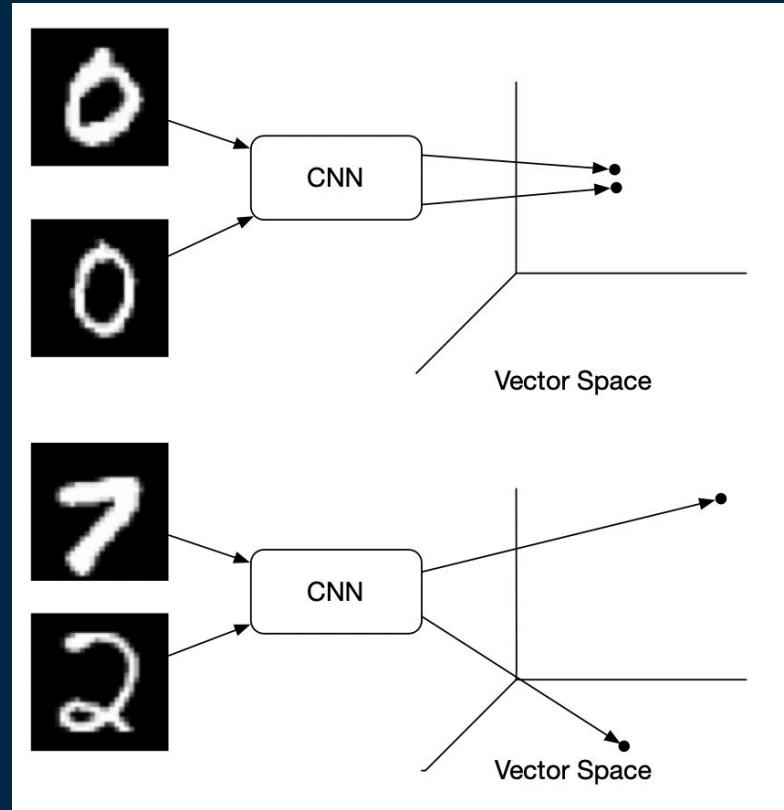
For positive pair  $(i,j)$  :

$$\text{softmax}(Z_i) = \frac{\exp(Z_i)}{\sum \exp(Z_i)}$$

Similarity of positive pair

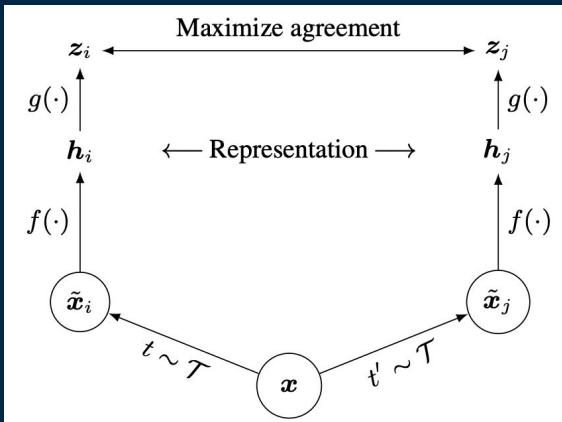
$$\ell_{i,j} = -\log \frac{\exp(\text{sim}(z_i, z_j)/\tau)}{\sum_{k=1}^{2N} [k \neq i] \exp(\text{sim}(z_i, z_k)/\tau)}$$

Similarity of negatives



# Key Idea: Augmentation

Generate augmentations for positive and negative samples



Batch of N images:

Two augs of same image

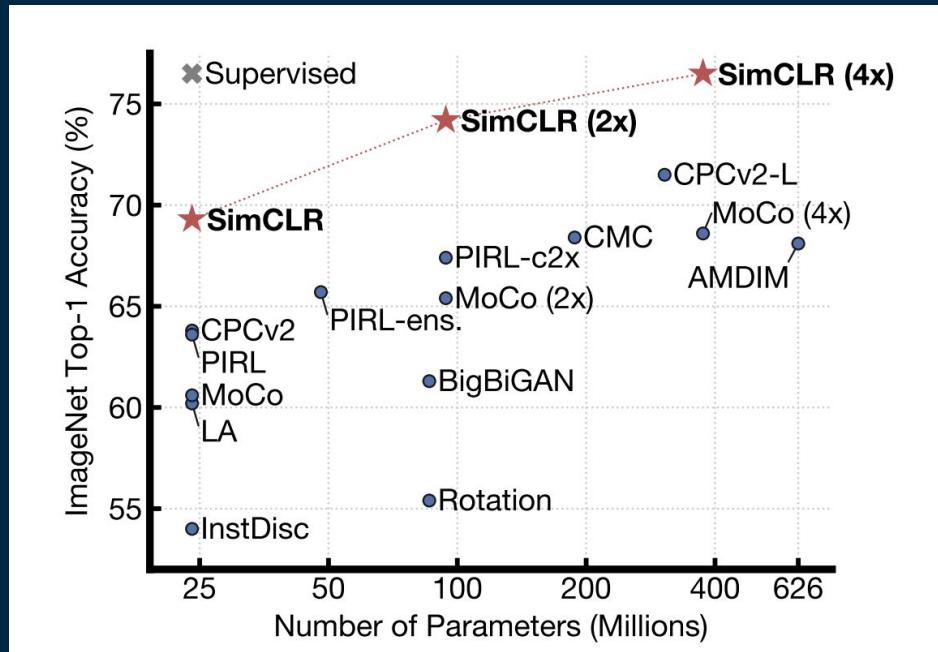
$$\ell_{i,j} = -\log \frac{\exp(\text{sim}(z_i, z_j)/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(\text{sim}(z_i, z_k)/\tau)}$$

All the other images in the batch

# Evaluation

Strong SS performance

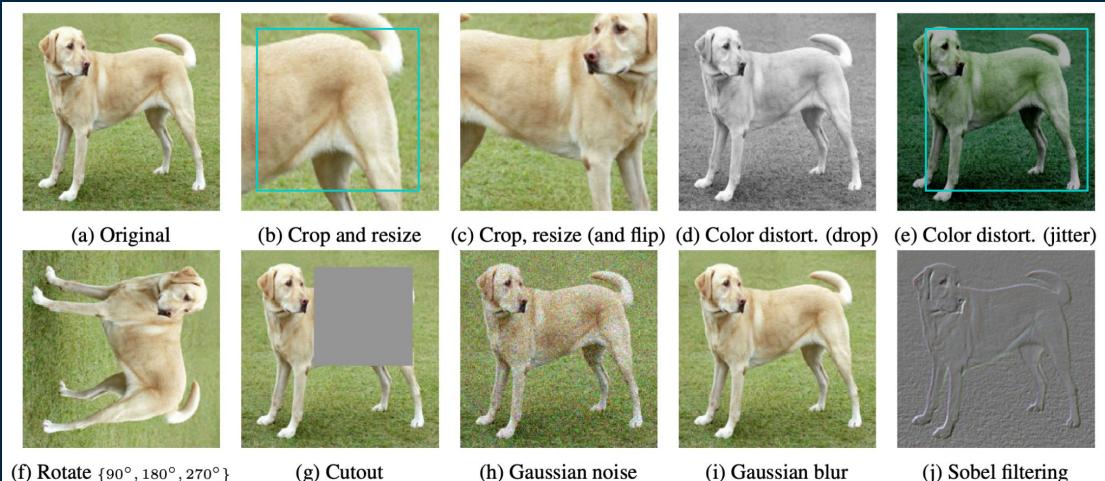
Method	Architecture	Label fraction		
		1%	10%	Top 5
Supervised baseline	ResNet-50	48.4	80.4	
<i>Methods using other label-propagation:</i>				
Pseudo-label	ResNet-50	51.6	82.4	
VAT+Entropy Min.	ResNet-50	47.0	83.4	
UDA (w. RandAug)	ResNet-50	-	88.5	
FixMatch (w. RandAug)	ResNet-50	-	89.1	
S4L (Rot+VAT+En. M.)	ResNet-50 (4×)	-	91.2	
<i>Methods using representation learning only:</i>				
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×)	<b>85.8</b>	<b>92.6</b>	



# Key Findings - Augmentation

Which augmentations matter?

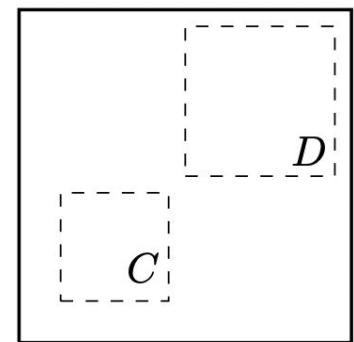
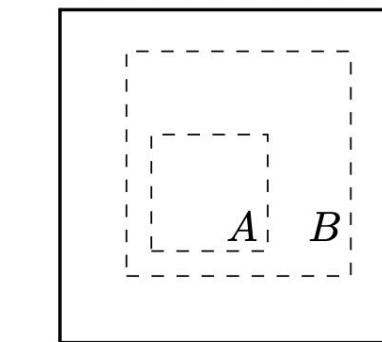
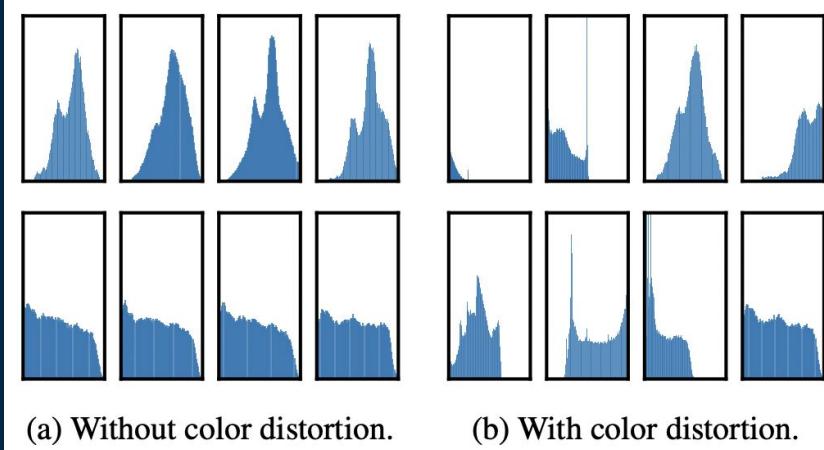
	Crop	Cutout	Color	Sobel	Noise	Blur	Rotate	Average
1st transformation	33.1	33.9	56.3	46.0	39.9	35.0	30.2	39.2
Crop	32.2	25.6	33.9	40.0	26.5	25.2	22.4	29.4
Color	55.8	35.5	18.8	21.0	11.4	16.5	20.8	25.7
Sobel	46.2	40.6	20.9	4.0	9.3	6.2	4.2	18.8
Noise	38.8	25.8	7.5	7.6	9.8	9.8	9.6	15.5
Blur	35.1	25.2	16.6	5.8	9.7	2.6	6.7	14.5
Rotate	30.0	22.5	20.7	4.3	9.7	6.5	2.6	13.8



# Key Findings - Augmentation

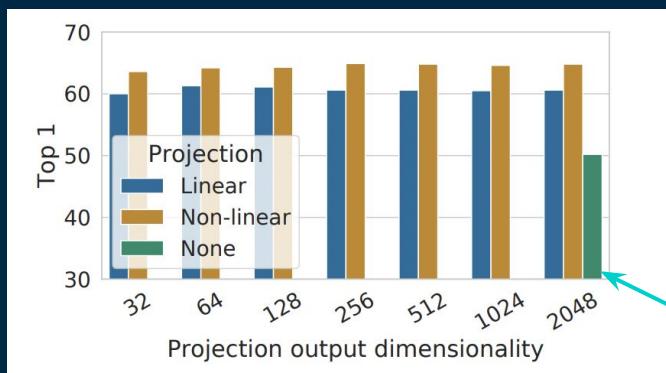
Why cropping?

Why and When to use color distortion?

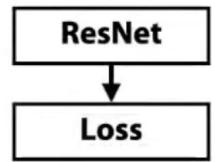


# Key Findings - Projection

None | Linear | Non-Linear

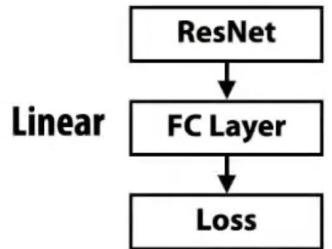


None



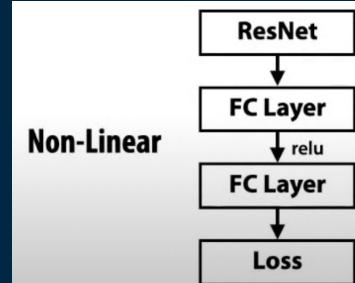
Not an  
error

Linear



USE THIS ONE!

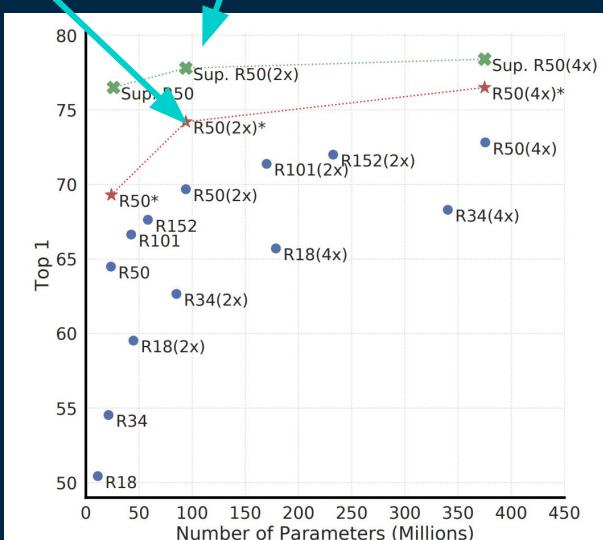
Non-Linear



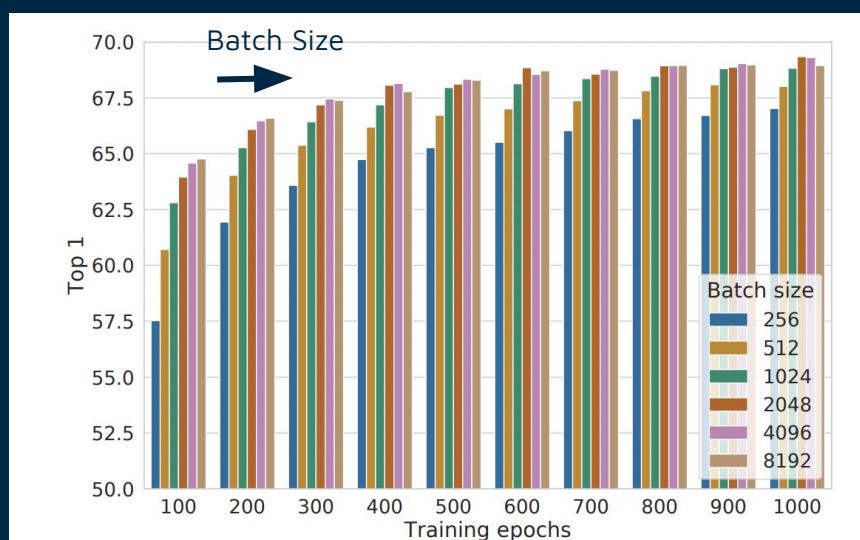
# Key Findings - Scale

SimSLR

ResNet



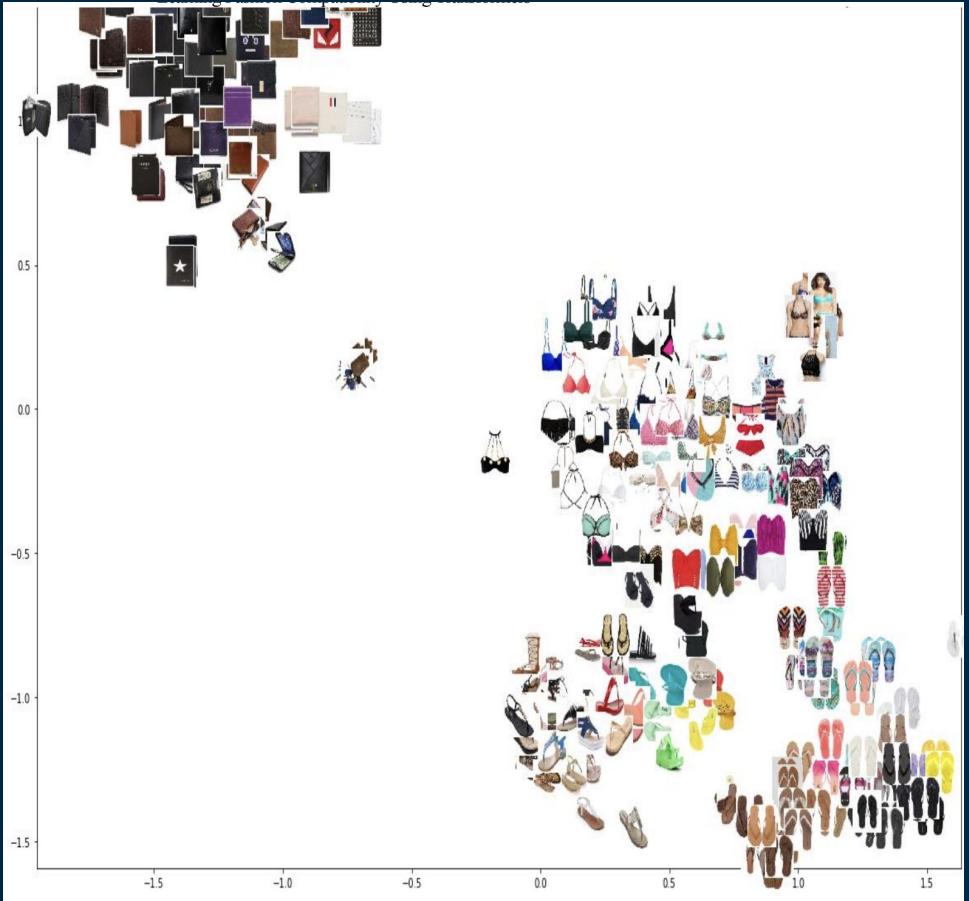
Model Size



Training time

# SimCLR on different dataset

Using SimCLR on a unique fashion dataset



# SLL with LANGUAGE MODELS



## From the article: [DistilBERT](#)

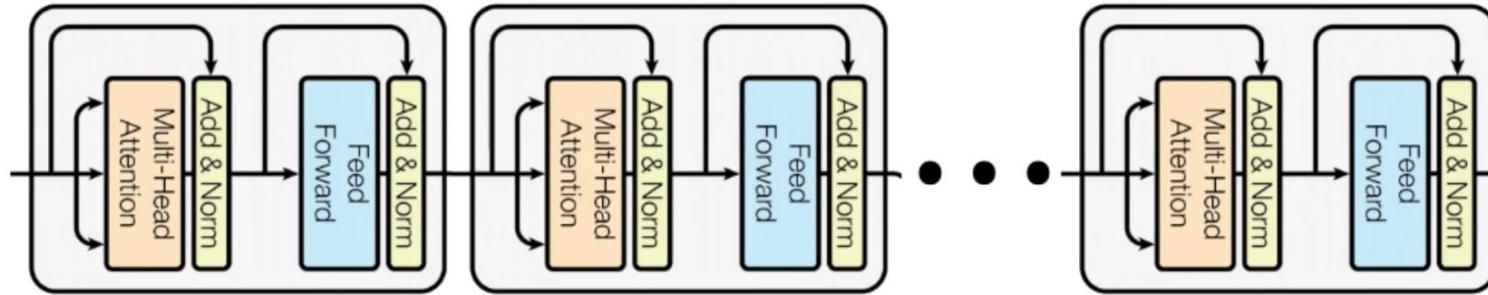


# 8,300,000,000

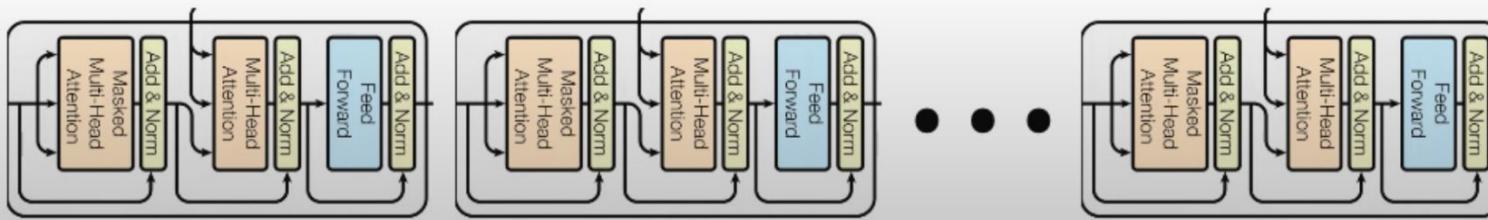
MEGATRON-LM



BERT



GPT



# BERT

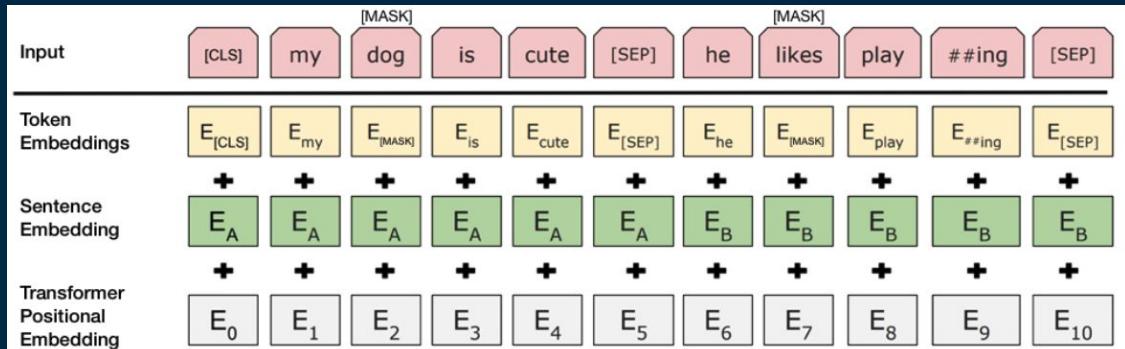
(Google, October 2018)

## Bidirectional Encoder Representations from Transformers

### PRETRAIN

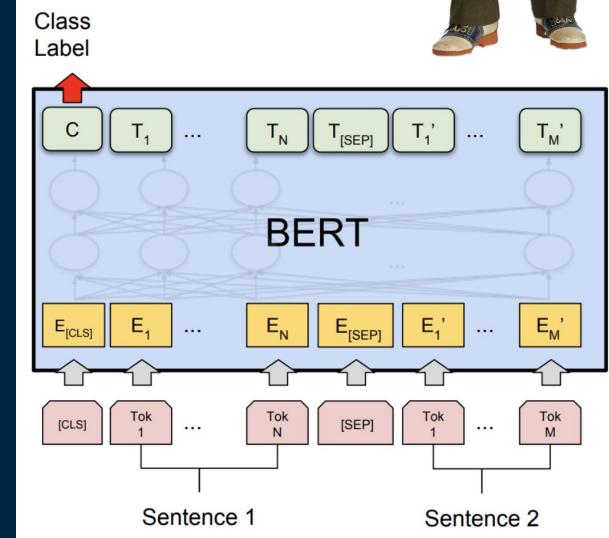
Mask Language Modeling (MLM)  
Bank of <mask> river.

Next Sentence Prediction (NSP)  
Data Science is cool. I like it.



### FINE TUNE

Add FC layer on top of BERT  
Train on Classification, Q&A, etc.



# GPT-3 (OpenAI, May 2020)

## Language Models are Few-Shot Learners

### Zero-Shot

The model predicts the answer given only a natural language description.

No gradient updates are performed.

### One-Shot

In addition to the task description, the model sees a single example of the task.

No gradient updates are performed.

### Few-Shot

In addition to the task description, the model sees a few examples of the task.

No gradient updates are performed.

1 Translate English to French: ← *task description*  
2 cheese => ..... ← *prompt*

1 Translate English to French: ← *task description*  
2 sea otter => loutre de mer ← *example*  
3 cheese => ..... ← *prompt*

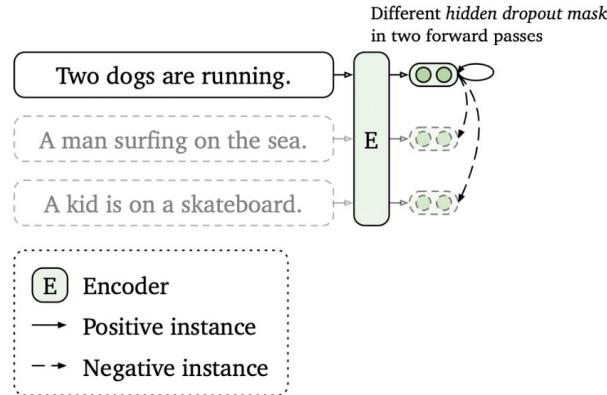
1 Translate English to French: ← *task description*  
2 sea otter => loutre de mer ← *examples*  
3 peppermint => menthe poivrée  
4 plush girafe => girafe peluche  
5 cheese => ..... ← *prompt*

# SimCSE (May 2022)

## Simple Contrastive Learning of Sentence Embeddings

### Augmentation - Dropout

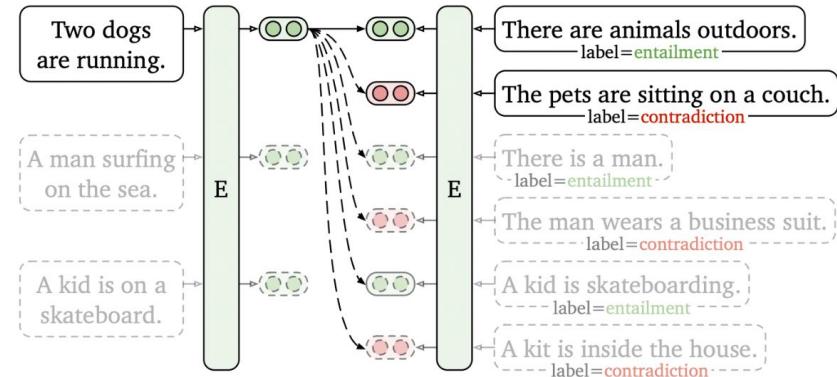
(a) Unsupervised SimCSE



### Augmentation

Synonyms, Vocabulary, Translation, etc.

(b) Supervised SimCSE



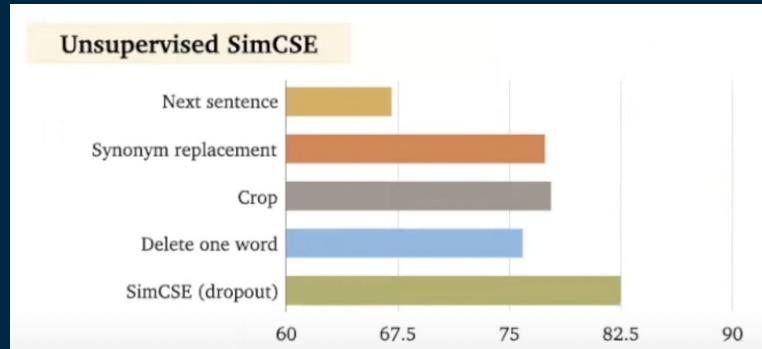
$$\ell_i = -\log \frac{e^{\text{sim}(\mathbf{h}_i, \mathbf{h}_i^+)/\tau}}{\sum_{j=1}^N e^{\text{sim}(\mathbf{h}_i, \mathbf{h}_j^+)/\tau}}$$

Similarity function Sentence embedding Temperature  
Positive pairs Negative pairs

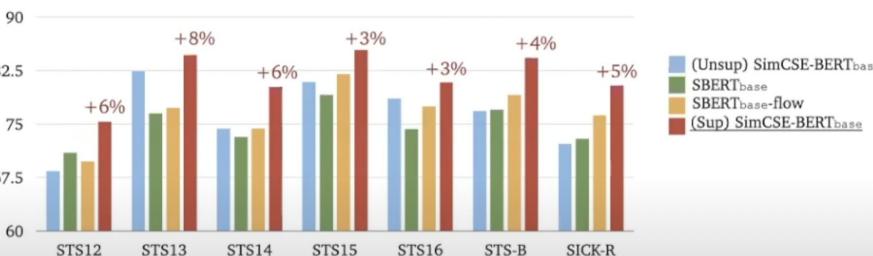
# SimCSE (May 2022)

## Simple Contrastive Learning of Sentence Embeddings

- Contrastive Learning improve pretrained Embedding
- Use Alignment and Uniformity to analyze different pairs

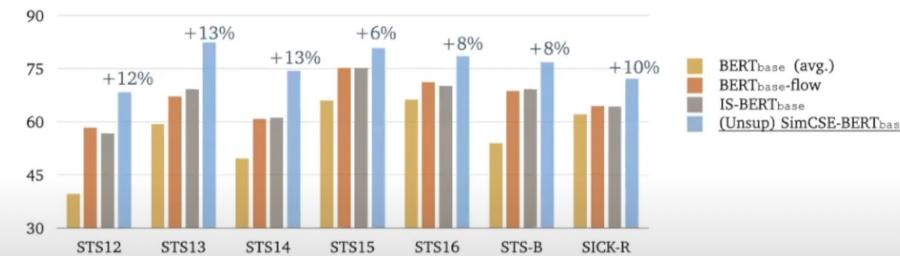


Semantic textual similarity (STS) tasks: Spearman's correlation



Even unsupervised SimCSE matches supervised SentenceBERT  
6.7% higher than SentenceBERT using the same NLI datasets

Semantic textual similarity (STS) tasks: Spearman's correlation



~10% higher than previous SOTA  
~20% higher than avg. BERT embeddings

# RECAP

SSL

WHAT IS SSL?



Learning from data

SimCLR

Article Review



Training, Evaluation, Findings

NLP

SLL in LANGUAGE MODELs



BERT, GPT-X, SimCSE, etc.

Do you have any questions?

SAHAR.MILIS@google.com

<https://github.com/saharmilis/>  
<https://medium.com/@sahar.millis>

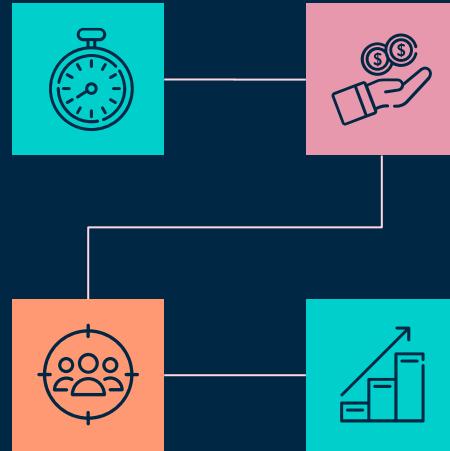
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# BERT – Bidirectional Encoder Representations from Transformers

NLP  
PROCESS THE DATA



NLU  
UNDERSTAND  
LANGUAGE

TAKS  
Let's talk about it :)

# UNDERSTANDING THE PROBLEM

## MARS

Despite being red, Mars is a cold place. It's full of iron oxide dust, which gives the planet its reddish cast

## VENUS

Venus has a beautiful name and is the second planet from the Sun. It's terribly hot, even hotter than Mercury



# MAIN COMPETITORS

## NEPTUNE

It's the farthest planet from the Sun

## MARS

Despite being red, Mars is a cold place

## VENUS

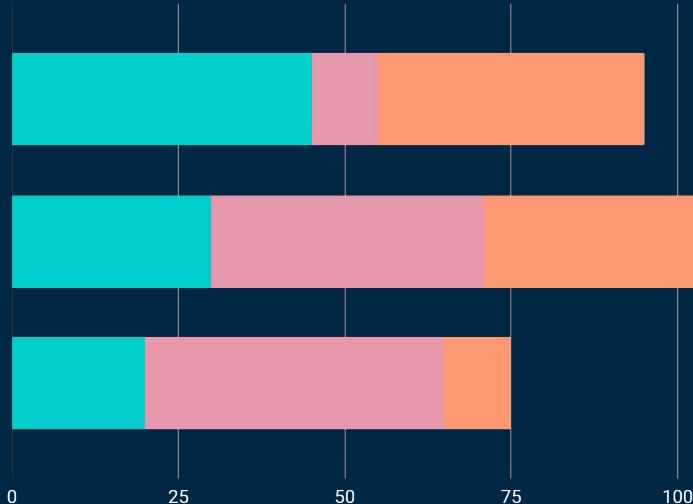
Venus is the second planet from the Sun

## SATURN

It's composed mostly of hydrogen and helium



# MARKET RESEARCH



## NEPTUNE

It's the farthest planet from the Sun



## MERCURY

Mercury is the closest planet to the Sun



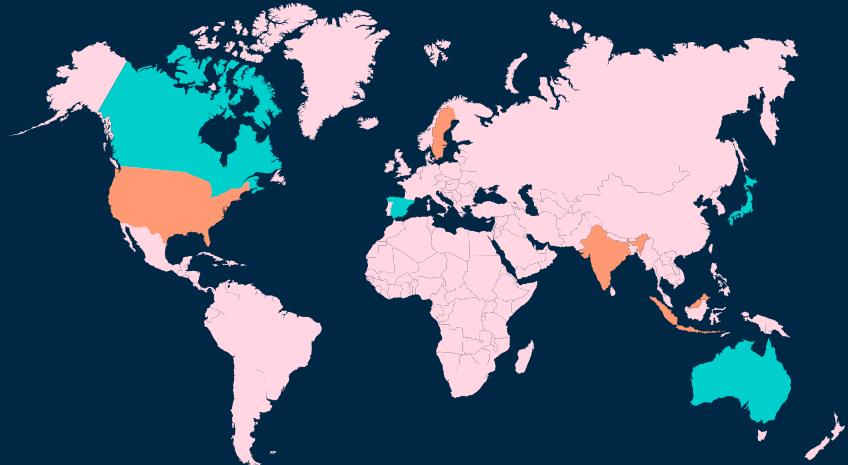
## SATURN

Saturn is composed of hydrogen and helium



# ANALYSIS

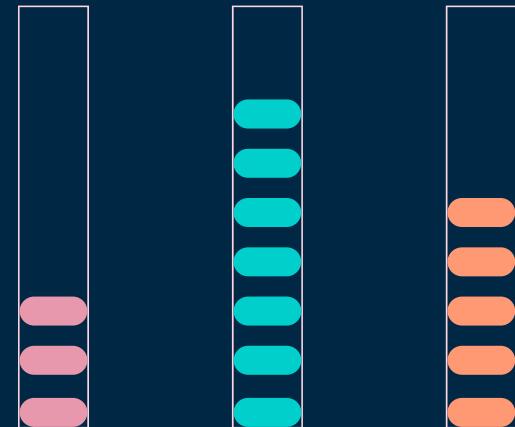
## OUTREACH



Mars

Mercury

## TOP RATED VALUES



30%

Saturn

80%

Neptune

50%

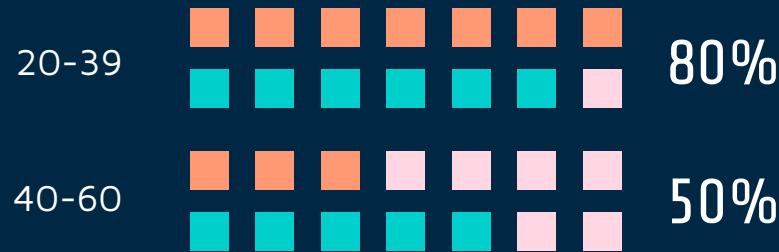
Venus

# TARGET

## GENDER



## AGE



A black and white photograph of two young women standing side-by-side, looking down at a tablet device held by the woman on the right. They are both smiling. The woman on the left has long blonde hair and is wearing a dark denim jacket over a white top. The woman on the right has curly dark hair and is wearing a light-colored cardigan over a t-shirt. The background is a bright, minimalist room with a white shelving unit.

A Picture Is Worth a  
Thousand Words



“This is a quote. Words full of wisdom that someone important said and can make the reader get inspired.”

—SOMEONE FAMOUS

# OUR PARTNERS

Venus has an extremely poisonous atmosphere

**VENUS**

**SATURN**

Saturn is composed mostly of hydrogen and helium



Despite being red, Mars is actually a cold place

**MARS**

**MERCURY**

Mercury is the closest planet to the Sun

# TESTIMONIALS



"Mercury is the closest planet to the Sun and the smallest of them all"

—RYAN DIXON



"Saturn is composed mostly of hydrogen and helium"

—BILLY BROOKS



"Venus has a beautiful name and is the second planet from the Sun"

—ALIYA FARLEY



"The Sun is the star at the center of the Solar System"

—LUCY JADE



"Jupiter is a gas giant and the biggest planet in the Solar System"

—HENRY McKANE



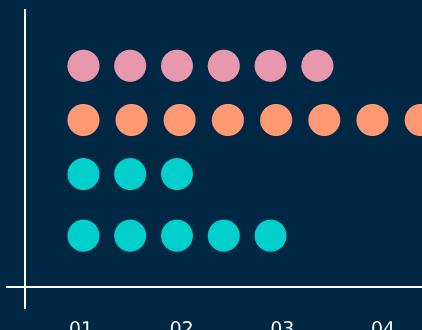
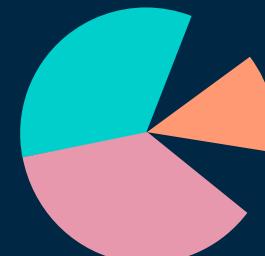
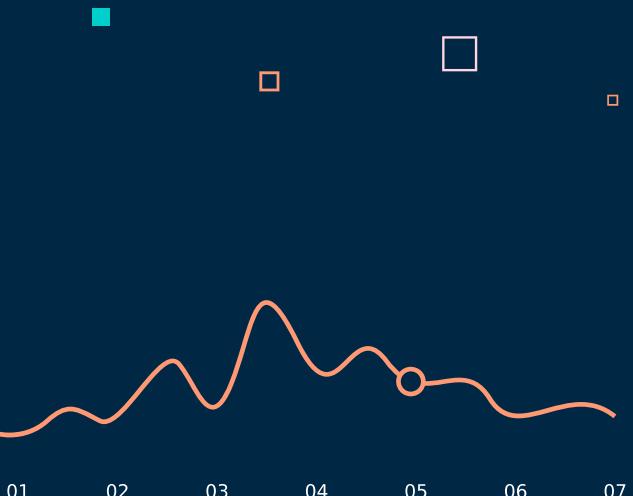
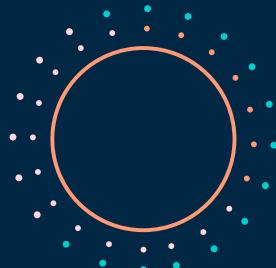
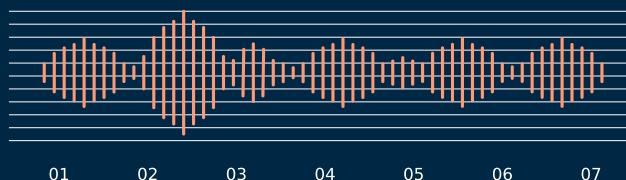
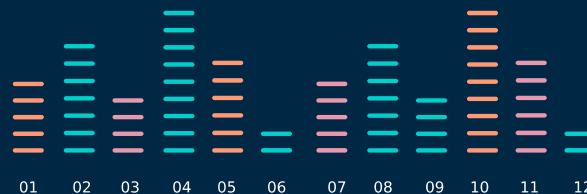
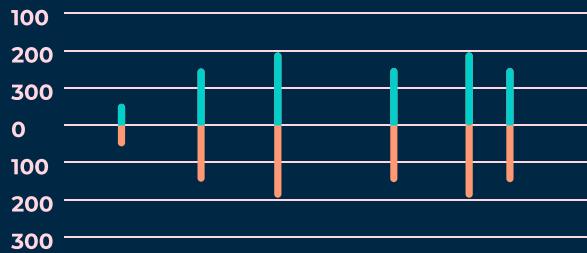
"Neptune is the fourth-largest planet in the Solar System"

—ROSE CLARK

# AWARDS

DATE	REASON	DESCRIPTION
2010	Jupiter	It's the closest planet to the Sun and the smallest one
2012	Neptune	Despite being red, Mars is actually a cold place
2016	Saturn	It has a nice name and is the second planet from the Sun

# ALTERNATIVE RESOURCES



# RESOURCES

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## VECTORS

- Abstract pixel rain blue background
- Dashboard element collection
- Red and blue neon fingerprint background
- Dashboard element collection template

## PHOTOS

- Female colleagues discussing work at office
- Close-up confident adult woman posing
- Portrait of beautiful adult woman smiling

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#ff9973

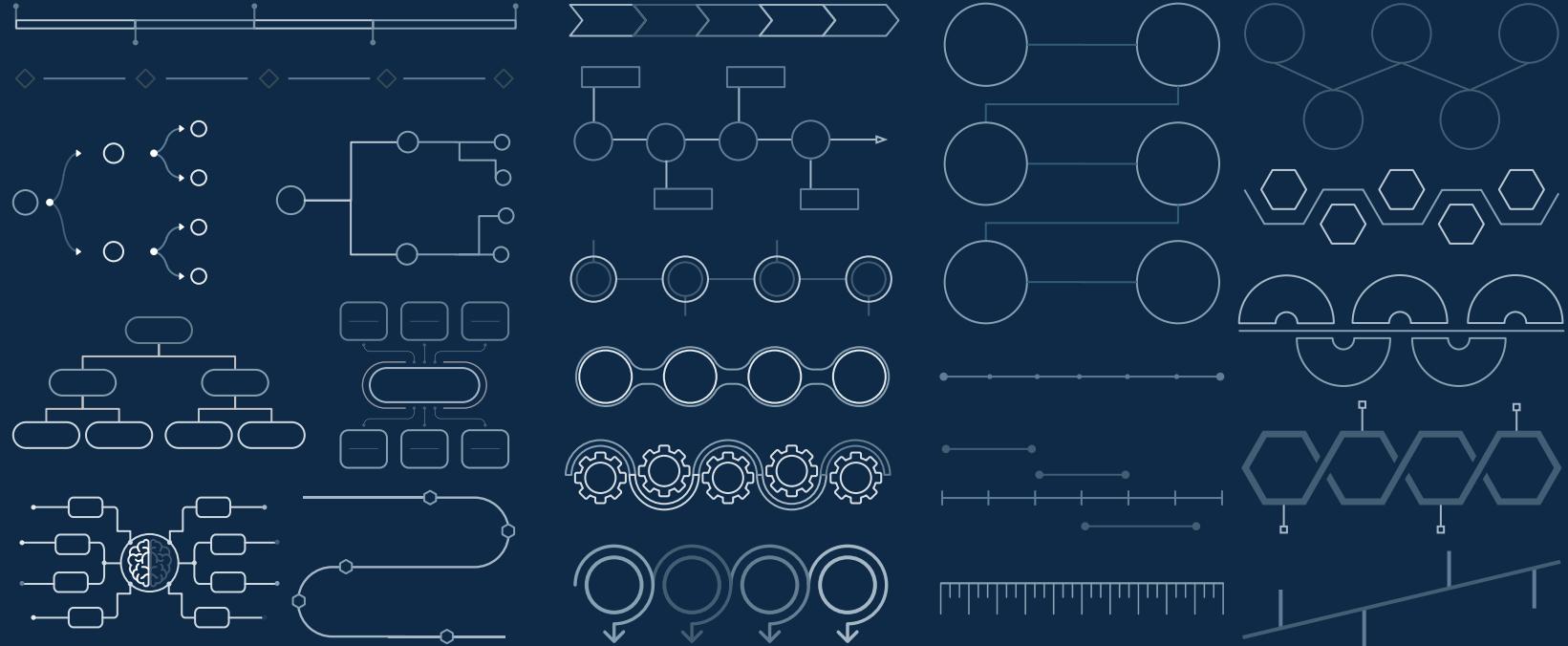
# Use our editable graphic resources...

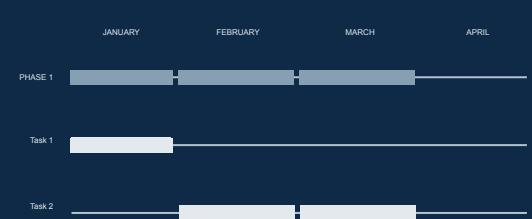
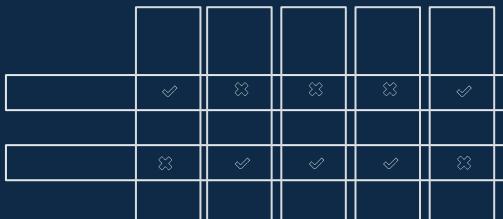
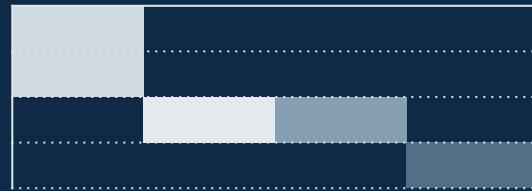
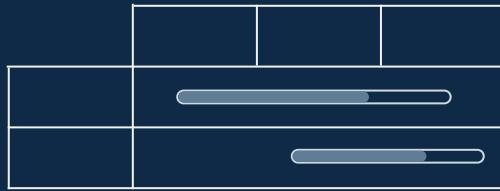
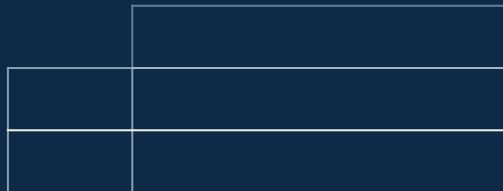
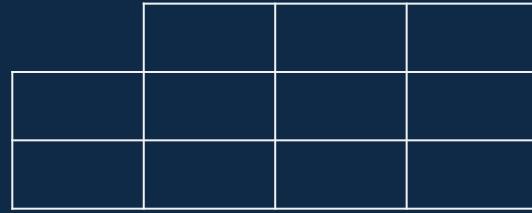
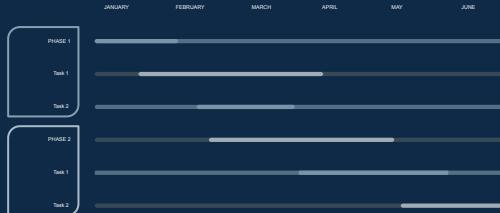
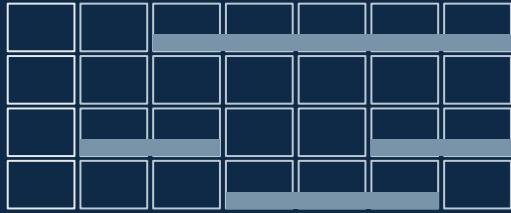
You can easily resize these resources without losing quality. To change the color, just ungroup the resource and click on the object you want to change. Then, click on the paint bucket and select the color you want.

Group the resource again when you're done.

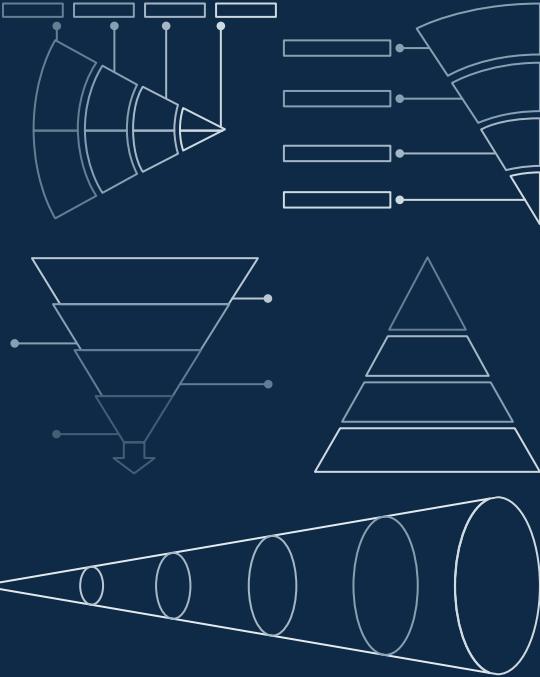
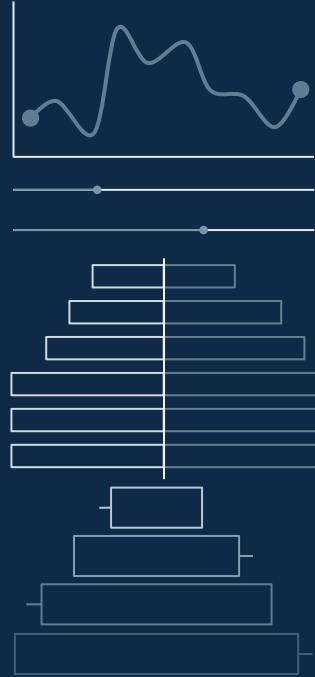
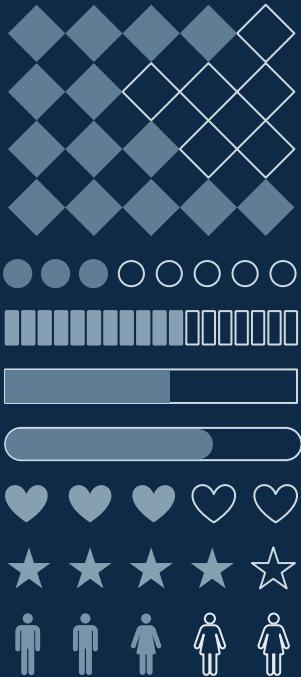
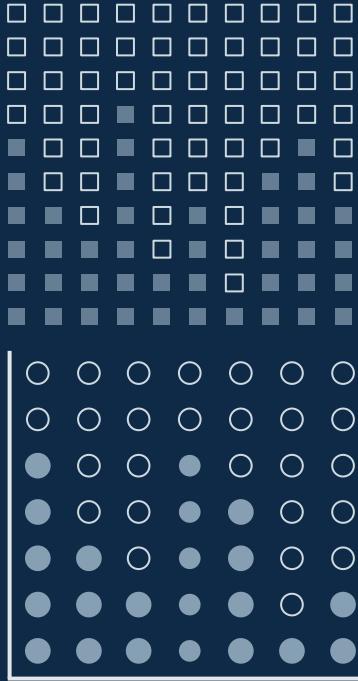












# ...and our sets of editable icons

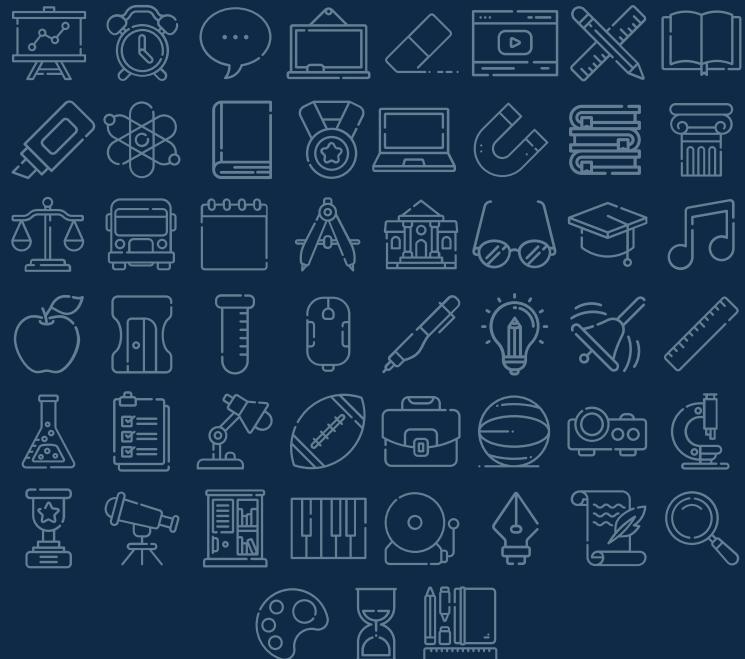
You can resize these icons without losing quality.

You can change the stroke and fill color; just select the icon and click on the paint bucket/pen.

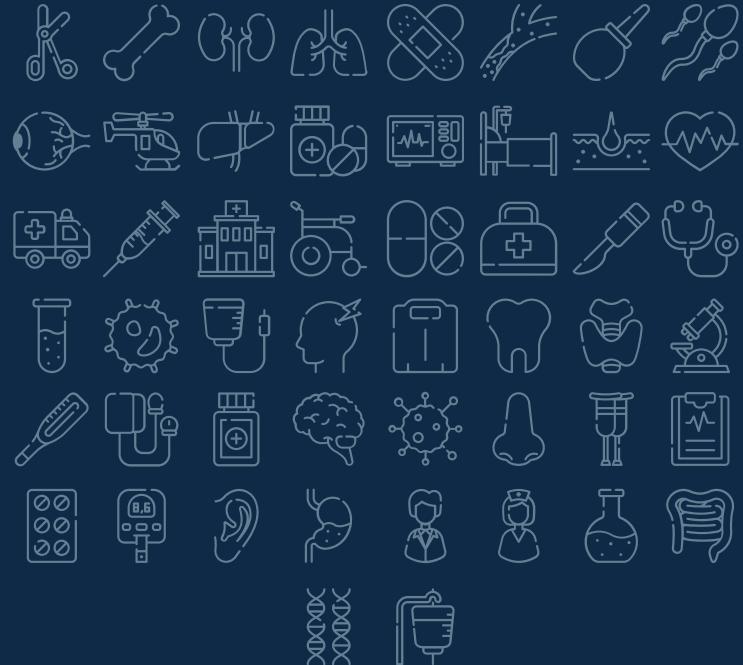
In Google Slides, you can also use Flaticon's extension, allowing you to customize and add even more icons.



## Educational Icons



## Medical Icons



## Business Icons



## Teamwork Icons



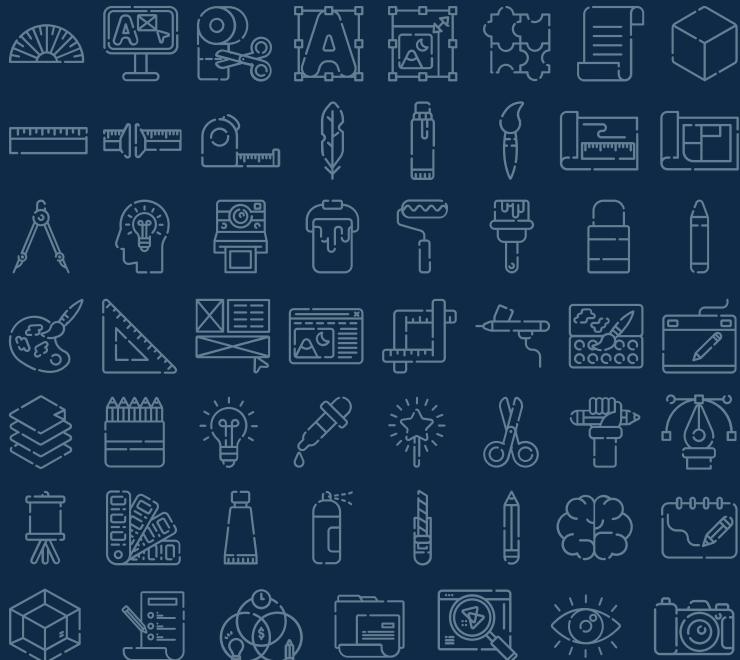
## Help & Support Icons



# Avatar Icons



## Creative Process Icons



## Performing Arts Icons



# Nature Icons



# SEO & Marketing Icons



