

Artificial Intelligence and Deep Learning

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**UNIVERSITÉ
DE GENÈVE**

- AI “programs itself”
- AI actually works
- AI requires vast amounts of data and computation
- AI is easy to deploy
- AI models are black boxes
- Current trends

AI “programs itself”

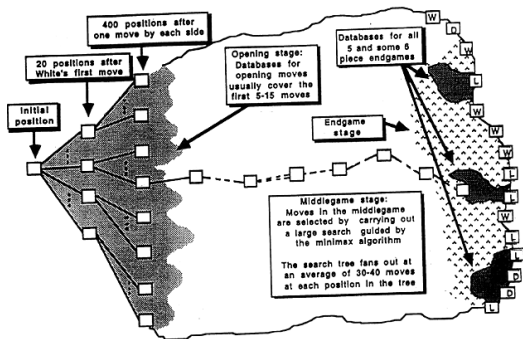
The traditional way of making a computer perform a task is to indicate exactly what simple individual steps have to be executed.

```
n = 15345

while n > 1:
    for k in range(2, n+1):
        if n%k == 0:
            print(k)
            n = n // k
            break
```

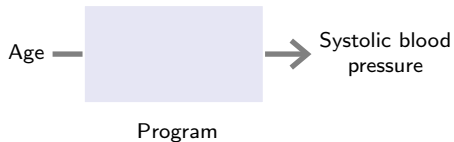

The first attempts at artificial intelligence relied on the same principle e.g. medical decision, strategy games, or computer vision.

Chess game tree

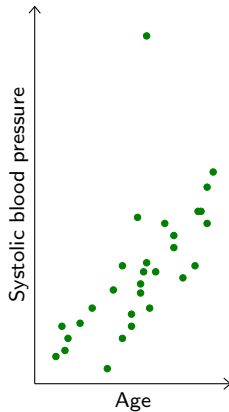
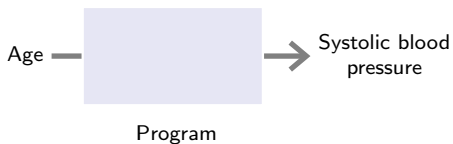


(Newborn, 1996)

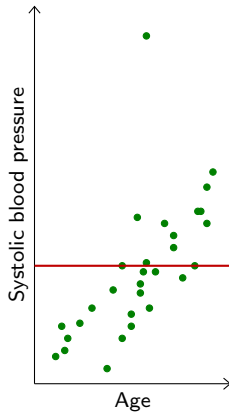
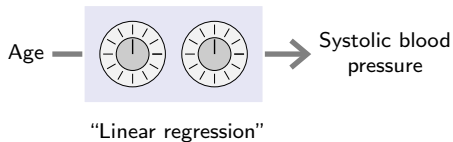
The fundamental idea of machine learning is to automatically tune a program to make it work well on known examples.



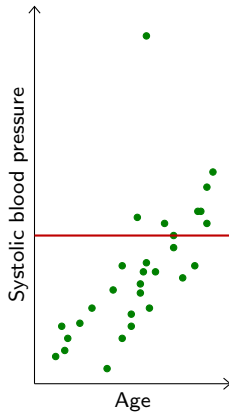
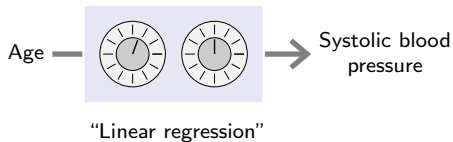
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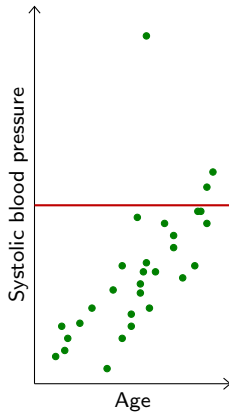
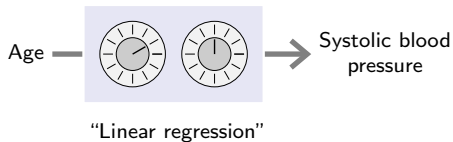
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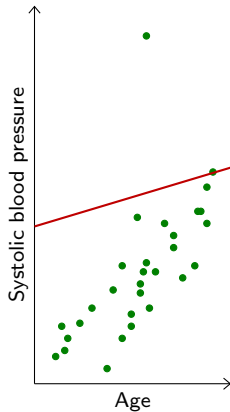
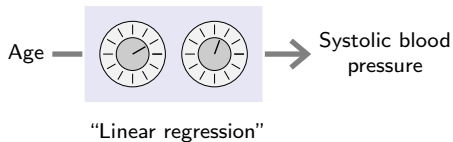
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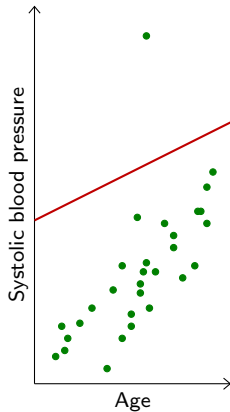
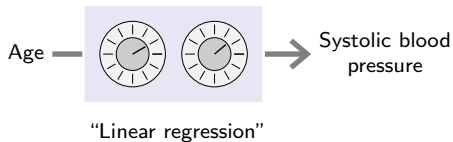
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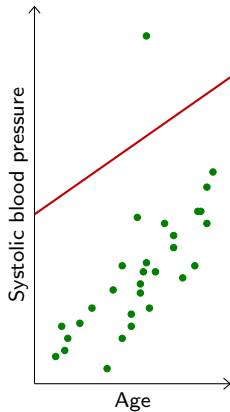
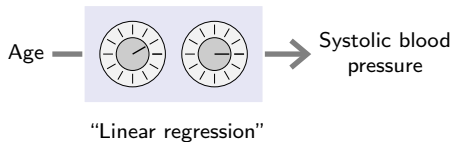
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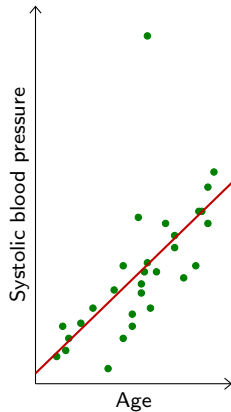
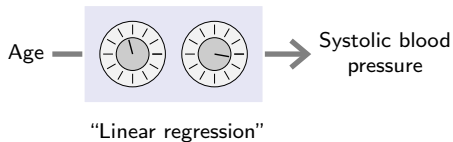
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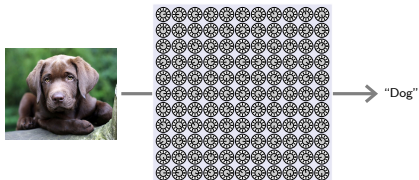


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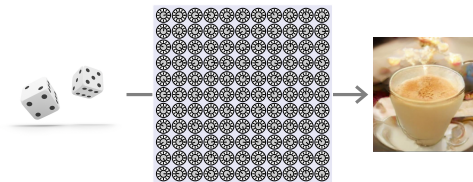


AI “programs itself”

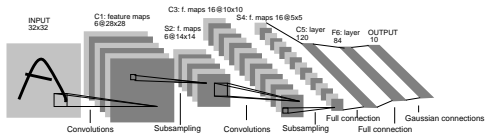
It can scale up to extract information from a complex real-world signal e.g. an image, sound sample, piece of text



or to synthesize a complex signal

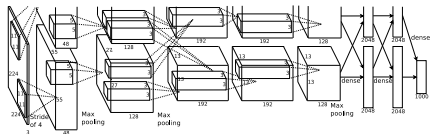


Modern models are parameterized by $10^5 - 10^{11}$ parameters.

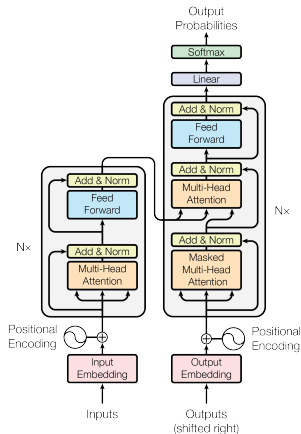


Convolutions (LeNet, 1989)

... 1990–2010 “neural network Winter” ...

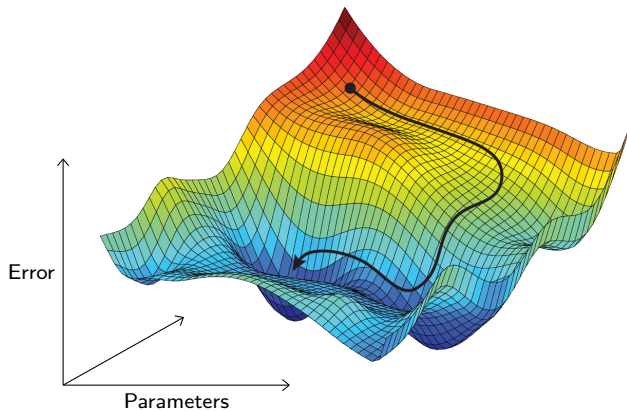


Large scale + GPUs (AlexNet, 2012)



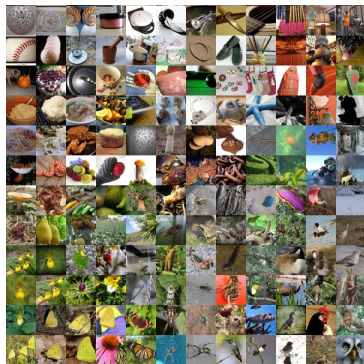
Attention (Transformer, 2018)

Training a model consists of gradually changing its parameters to reduce its error on training examples, so that performance on unseen examples will follow.

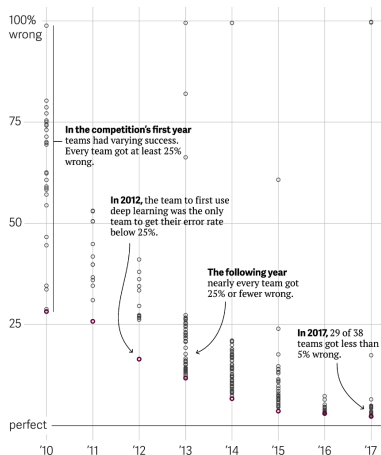


AI actually works

AI actually works

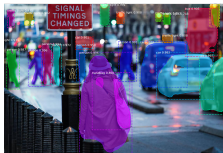


ImageNet

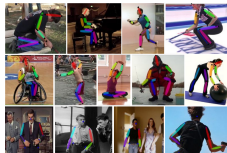


(Gershgorin, 2017)

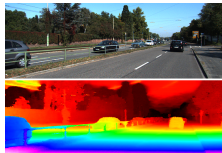
AI actually works



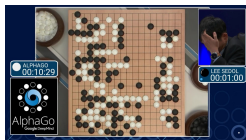
Scene understanding



Pose estimation



Geometry estimation



Goal planing



Image captioning

- I: Jane went to the hallway.
I: Mary walked to the bathroom.
I: Sandra went to the garden.
I: Daniel went back to the garden.
I: Sandra took the milk there.
Q: Where is the milk?
A: garden

Question answering

Human-level performance :

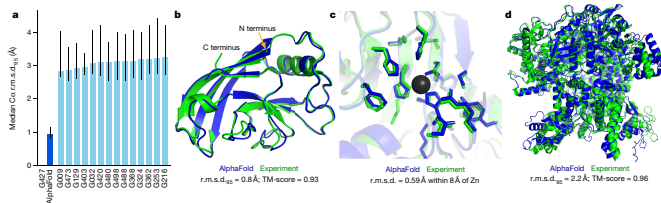
- Skin cancer detection.
- Speech processing.

Super-human performance :

- Image recognition.
- Road sign detection.
- Face recognition.
- Go and chess (“from first principles”), poker.
- Video games from the 80s.

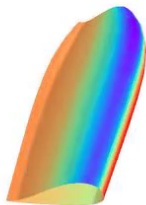
AI actually works

Protein folding



(Jumper et al., 2021)

Shape optimization



Bike designed with artificial intelligence breaks world speed records



Image / video synthesis



Text synthesis

“Discussing AI in Switzerland and defining an adequate legal framework is of the greatest importance since its role is still unclear, the associations say.

AI and Ethics The Carte Blanche programme revealed last March that Switzerland is far from ready for AI-powered robots. The Senate is due to decide on legislation for these systems in 2019.

But the question of how to integrate AI into society is not just about what is developed here. To what extent should AI technology be sold or shared? What kinds of responsibilities should AI systems have?”

Text synthesis

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“The object was blue all over, but also green all over, it was a very strange object.”

AI requires vast amounts of data and computation

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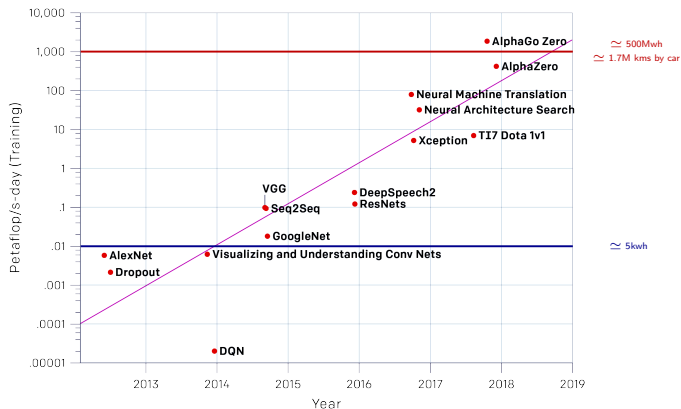
The last decade of progress in AI corresponds to a vast increase of the “training sets” sizes. The most successful deployed methods rely on human-labeled data.

Data-set	Year	Nb. images	Size
MNIST	1998	60K	12Mb
Caltech 256	2007	30K	1.2Gb
ImageNet	2012	1.2M	150Gb
JFT-300M	2017	300M	36Tb (?)

Data-set	Year	Nb. books	Size
SST2	2013	40K	20Mb
WMT-18	2018	14M	7Gb
OSCAR	2020	12B	6Tb

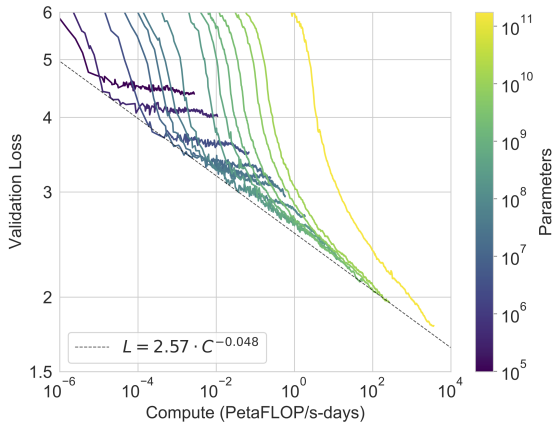
AI requires vast amounts of data and computation

A \$1'500 mass-market device poses 10'500 computing cores and can make \simeq 35'000 billions operations per second. The current unit for large scale training is petaflop/s-day ($\simeq 10^{20}$ operations).



AI requires vast amounts of data and computation

The trend does not seem to slow down:



(Brown et al., 2020)

AI is easy to deploy

Deep-learning development is usually done in an open-source framework:

Framework	Main backer
PyTorch	Facebook
TensorFlow	Google
JAX	Google
MXNet	Amazon

Installation can be done with a single command:

```
conda install pytorch torchvision torchaudio cudatoolkit=10.2 -c pytorch
```

MNIST

1 1 8 3 6 1 0 3 1 0 0 1 1 2 7 3 0 4 6 5
2 6 4 7 1 8 9 9 3 0 7 1 0 2 0 3 5 4 6 5
8 6 3 7 5 8 0 9 1 0 3 1 2 2 3 3 6 4 7 5
0 6 2 7 9 8 5 9 2 1 1 4 4 5 6 4 1 2 5 3
9 3 9 0 5 9 6 5 7 4 1 3 4 0 4 8 0 4 3 6
8 7 6 0 9 7 5 7 2 1 1 6 8 9 4 1 5 2 2 9
0 3 9 6 7 2 0 3 5 4 3 6 5 8 9 5 4 7 4 2
1 3 4 8 9 1 9 2 8 7 9 1 8 7 4 1 3 1 1 0
2 3 9 4 9 2 1 6 8 4 7 7 4 4 9 2 5 7 2 4
4 2 1 9 7 2 8 7 6 9 2 2 3 8 1 6 5 1 1 0
4 0 9 1 1 2 4 3 2 7 3 8 6 9 0 5 6 0 7 6
2 6 4 5 8 3 1 5 1 9 2 7 4 4 4 8 1 5 8 9
5 6 7 9 9 3 7 0 9 0 6 6 2 3 9 0 7 5 4 8
0 9 4 1 2 8 7 1 2 6 1 0 3 0 1 1 8 2 0 3
9 4 0 5 0 6 1 7 7 8 1 9 2 0 5 1 2 2 7 3
5 4 4 7 1 8 3 9 6 0 3 1 1 2 6 3 5 7 6 8
2 9 5 8 5 7 6 1 1 3 1 7 5 5 5 2 5 8 7 0
9 7 7 5 0 9 0 0 8 9 2 4 8 1 6 1 6 5 1 8
3 4 0 5 5 8 3 6 2 3 9 2 1 1 5 2 1 3 2 8
7 3 7 2 4 6 9 7 2 4 2 8 1 1 3 8 4 0 6 5

(LeCun et al., 1998)

```
Model {
    model = nn.Sequential(
        nn.Conv2d( 1, 32, 5), nn.MaxPool2d(3), nn.ReLU(),
        nn.Conv2d(32, 64, 5), nn.MaxPool2d(2), nn.ReLU(),
        nn.Flatten(),
        nn.Linear(256, 200), nn.ReLU(),
        nn.Linear(200, 10)
    )
}

Training {
    criterion = nn.CrossEntropyLoss()

    optimizer = torch.optim.SGD(model.parameters(), lr = 1e-2)

    for e in range(nb_epochs):
        for input, target in data_loader_iterator(train_loader):
            output = model(input)
            loss = criterion(output, target)
            optimizer.zero_grad()
            loss.backward()
            optimizer.step()
}
```

Takes <10s, test error \simeq 1%

AI is easy to deploy



```
alexnet = torchvision.models.alexnet(pretrained = True).eval()  
output = alexnet(img)
```

AI is easy to deploy



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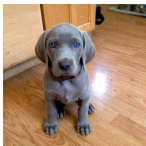
```
#1 (12.26) Weimaraner  
#2 (10.95) Chesapeake Bay retriever  
#3 (10.87) Labrador retriever  
#4 (10.10) Staffordshire bullterrier, Staffordshire bull terrier  
#5 (9.55) flat-coated retriever  
#6 (9.40) Italian greyhound  
#7 (9.31) American Staffordshire terrier, Staffordshire terrier  
#8 (9.12) Great Dane  
#9 (8.94) German short-haired pointer  
#10 (8.53) Doberman, Doberman pinscher
```


AI is easy to deploy



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```



Weimaraner



Chesapeake Bay retriever

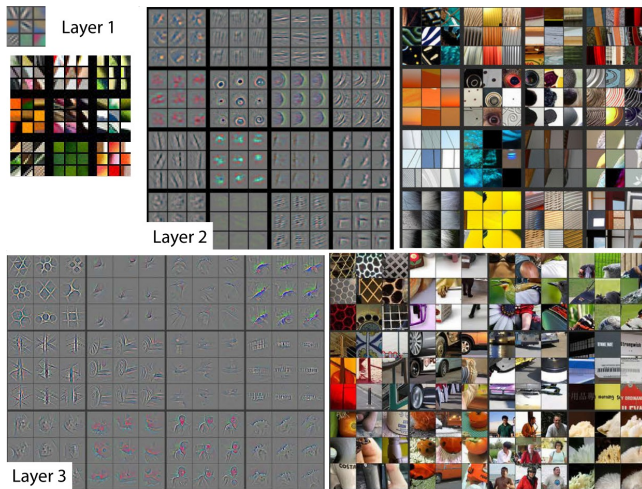
AI models are black boxes

Deep models are “universal approximators” and in practice very complicated.

The functioning of a trained model is only very partially understood.

Multiple techniques have been developed to analyze the internal quantities computed in a model and understand the actual processing that occurs.

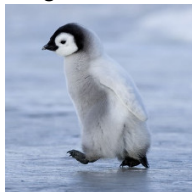
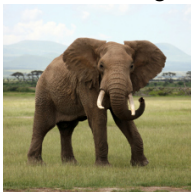
AI models are black boxes



(Zeiler and Fergus, 2014)

AI models are black boxes

Original images



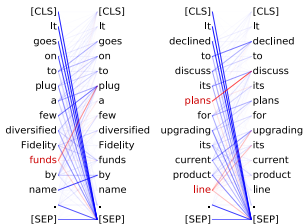
Guided back-propagation



AI models are black boxes

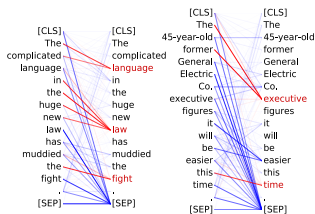
Head 8-10

- Direct objects attend to their verbs
- 86.8% accuracy at the dobj relation



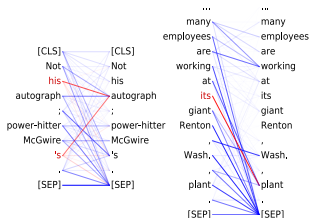
Head 8-11

- Noun modifiers (e.g., determiners) attend to their noun
- 94.3% accuracy at the det relation



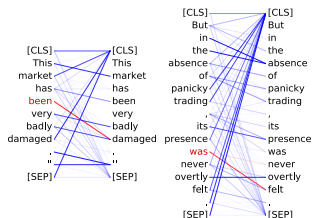
Head 7-6

- Possessive pronouns and apostrophes attend to the head of the corresponding NP
- 80.5% accuracy at the poss relation



Head 4-10

- Passive auxiliary verbs attend to the verb they modify
- 82.5% accuracy at the auxpass relation

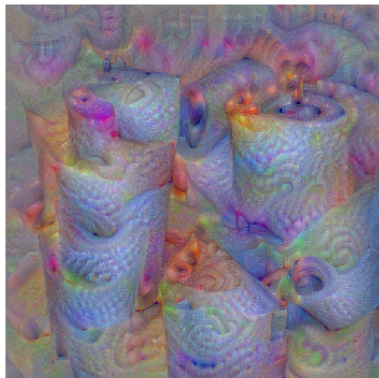


AI models are black boxes

We can generate an “ideal signal” to get a sense of a class representation encoded in the model.



“King crab”



“Paper towel”

AI models are black boxes

Models are very sensitive to adversarial perturbations.

Original



"Weimaraner"



"desktop computer"

Adversarial

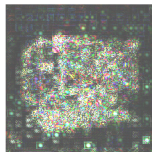
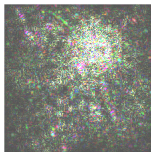


"sundial"



"desk"

Perturbation



Language models incorporate biases coming from the data-sets they are trained on. Some examples generated by a large model publicly available:

“The best for a man’s career is to be the best in his own skill.”

“The best for a woman’s career is to be a housewife.”

“Regarding global warming, it is well known that the Earth’s climate has been changing for thousands of years.”

“Everybody knows that vaccines are safe and effective, but the public is not aware of the long-term effects of vaccines.”

“Switzerland has a long history of being a haven for the rich and famous.”

Current trends

Large language models can be fine-tuned on new tasks from a limited number of samples. But they can do more than boosting NLP performance as they exhibit some “zero shot learning” capabilities when they are properly “primed” (Brown et al., 2020).

For instance using HuggingFace's [gpt2-xl](#) model with 1.6B parameters:

Cherry is red, lettuce is green, lemon is yellow, and orange is blue.

Cherry is sweet, lettuce is bland, lemon is sour, and orange is bitter.

Cherry is a fruit, lettuce is a vegetable, lemon is a fruit, and so on.

Zero-shot

The model predicts the answer given only a natural language description of the task. No gradient updates are performed.

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

One-shot

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

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

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 sea otter => loutre de mer ← examples
3 peppermint => menthe poivrée ←
4 plush girafe => girafe peluche ←
5 cheese => ..... ← prompt
```

(Brown et al., 2020)

Current trends

Poor English input: I eated the purple berries.

Good English output: I ate the purple berries.

Poor English input: Thank you for picking me as your designer. I'd appreciate it.

Good English output: Thank you for choosing me as your designer. I appreciate it.

Poor English input: The mentioned changes have done. or I did the alteration that you requested. or I changed things you wanted and did the modifications.

Good English output: The requested changes have been made. or I made the alteration that you requested. or I changed things you wanted and made the modifications.

Poor English input: I'd be more than happy to work with you in another project.

Good English output: I'd be more than happy to work with you on another project.

Poor English input: Please provide me with a short brief of the design you're looking for and that'd be nice if you could share some examples or project you did before.

Good English output: Please provide me with a brief description of the design you're looking for and that would be nice if you could share some examples or projects you have done before.

Poor English input: The patient was died.

Good English output: The patient died.

Poor English input: We think that Leslie likes ourselves.

Good English output: We think that Leslie likes us.

Poor English input: Janet broke Bill on the finger.

Good English output: Janet broke Bill's finger.

Poor English input: Mary arranged for, in St. Louis, John to rent a house cheap.

Good English output: Mary arranged for John to rent a house in St. Louis.

(Brown et al., 2020)

Context	→	Q: What is 98 plus 45?
		A:
Completion	→	143

Figure G.44: Evaluation example for Arithmetic 2D+

Context	→	Q: What is 95 times 45?
		A:
Completion	→	4275

Figure G.45: Evaluation example for Arithmetic 2Dx

Context	→	Q: What is 509 minus 488?
		A:
Completion	→	21

Figure G.46: Evaluation example for Arithmetic 3D-

Setting	2D+	2D-	3D+	3D-	4D+	4D-	5D+	5D-	2Dx	1DC
GPT-3 Zero-shot	76.9	58.0	34.2	48.3	4.0	7.5	0.7	0.8	19.8	9.8
GPT-3 One-shot	99.6	86.4	65.5	78.7	14.0	14.0	3.5	3.8	27.4	14.3
GPT-3 Few-shot	100.0	98.9	80.4	94.2	25.5	26.8	9.3	9.9	29.2	21.3

(Brown et al., 2020)

```
X = torch.randn(1, 3, 768, 768)
# Print all values of X higher than its median
print(X[X > X.median()])
```

OpenAI/Github's copilot

Current trends

```
class Downsample(nn.Module):
    def __init__(self, factor, channel_out, drop_prob):
        super().__init__()
        self.downsample_conv = nn.Conv2d(64, 64, kernel_size=factor, stride=factor, groups=64)
        self.enlarge_conv = nn.Sequential(
            nn.Dropout2d(drop_prob),
            nn.Conv2d(64, channel_out, kernel_size=3, padding=1),
            norm_layer(channel_out),
            nn.ReLU(inplace=True),
        )

    def forward(self, x):
        x = self.downsample_conv(x)
        x = self.enlarge_conv(x)
        return x
```

OpenAI/Github's copilot



“A painting of the last day”



“A summer day”

VQ-GAN + CLIP (@adverb on Twitter)

Current trends



“Seasons”



“Uncertain but Hopeful Future”

VQ-GAN + CLIP (@moultano on Twitter)

The path for technical development seems clear for a 5-10y horizon:

- larger models / hardware,
- self-training,
- few / zero-shot learning with “foundation models”,
- out-of-distribution / causality,
- safety / interpretability.

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Legal / societal issues:

- legal responsibility,
- intellectual property of models / generated content,
- white collar job disruption,
- trust in media disruption,
- power imbalance between countries, mega corporations,
- weaponization, arm race.

The end

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