AI & Deep Learning

ACTL3143 & ACTL5111 Deep Learning for Actuaries

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UNSW SYDNEY

Lecture Outline

- **Artificial Intelligence**
- Deep Learning Successes (Images)
- Deep Learning Successes (Text)
- Classifying Machine Learning Tasks
- Neural Networks
- California House Price Prediction
- Our First Neural Network
- Force positive predictions
- Preprocessing
- Early Stopping

Different goals of AI

Artificial intelligence describes an agent which is capable of:

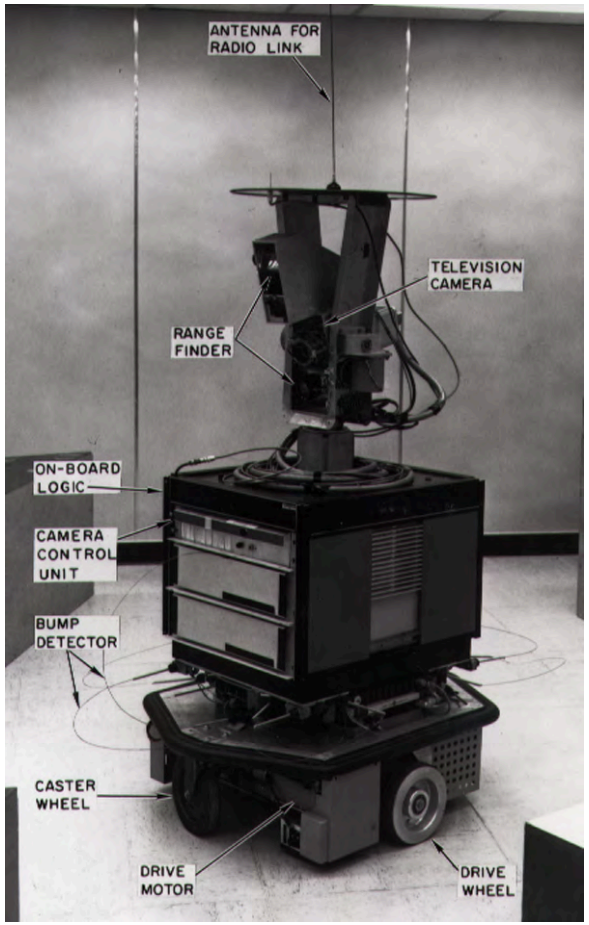
Thinking humanly	Thinking rationally
Acting humanly	Acting rationally

AI eventually become dominated by one approach, called *machine learning*, which itself is now dominated by *deep learning* (neural networks).

There are AI algorithms for simple tasks that don't use machine learning though.

You can study a 12 week course on AI and never touch on machine learning...

Shakey the Robot (~1966 – 1972)



Shakey the Robot

Source: Wikipedia page for the Shakey Project

Route-finding I

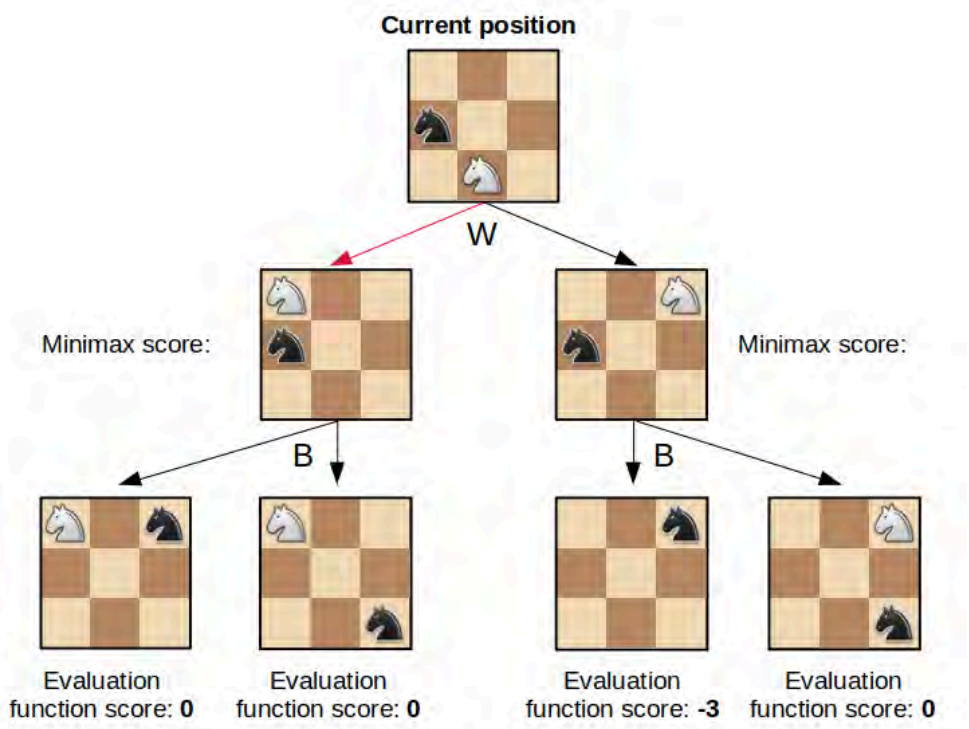
> At its core, a pathfinding method searches a graph by starting at one vertex and exploring adjacent nodes until the destination node is reached, generally with the intent of finding the cheapest route. Although graph searching methods such as a breadth-first search would find a route if given enough time, other methods, which "explore" the graph, would tend to reach the destination sooner. An analogy would be a person walking across a room; rather than examining every possible route in advance, the person would generally walk in the direction of the destination and only deviate from the path to avoid an obstruction, and make deviations as minor as possible. (Source: Wikipedia)

A* algorithm (1968).

Used in every GPS/Navigation app and...

Source: Wikipedia page for the A* search algorithm.

The minimax algorithm



The minimax algorithm for chess.

```
function minimax(position, depth, maximizingPlayer)
   if depth == 0 or game over in position
      return static evaluation of position

   if maximizingPlayer
      maxEval = -infinity
      for each child of position
         eval = minimax(child, depth - 1, false)
         maxEval = max(maxEval, eval)
      return maxEval

   else
      minEval = +infinity
      for each child of position
         eval = minimax(child, depth - 1, true)
         minEval = min(minEval, eval)
      return minEval
```

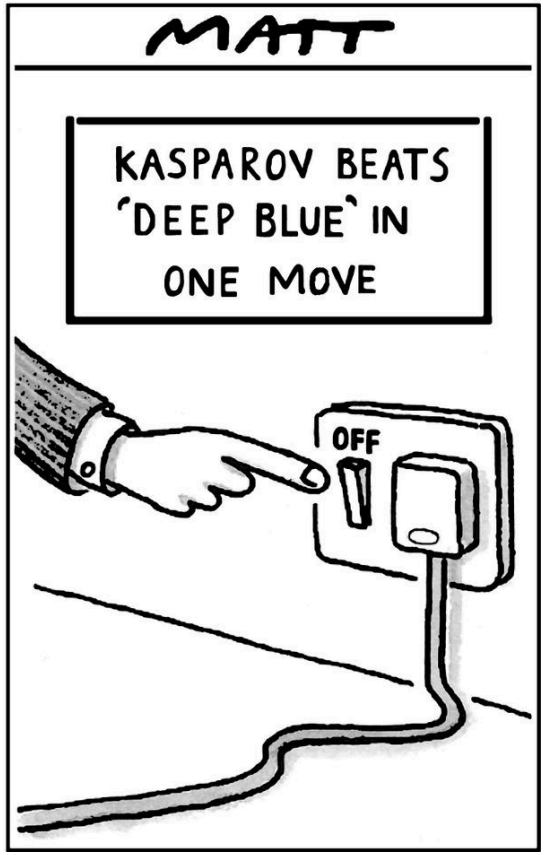
Pseudocode for the minimax algorithm.

Source: codeRtime, Programming a simple minimax chess engine in R, and Sebastian Lague (2018), Algorithms Explained – minimax and alpha-beta pruning.

Chess

Deep Blue (1997)

Gary Kasparov playing Deep Blue.



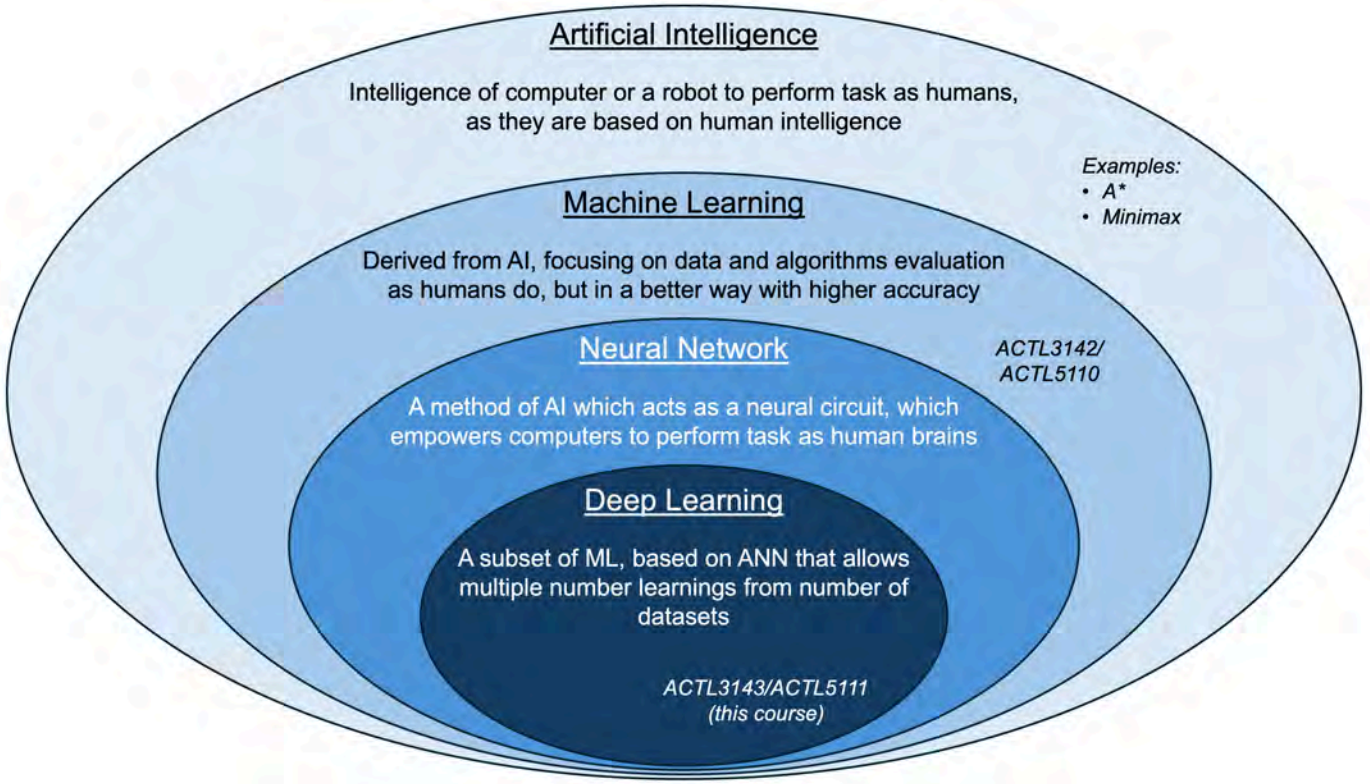
Cartoon of the match.

Sources: Mark Robert Anderson (2017), Twenty years on from Deep Blue vs Kasparov, The Conversation article, and Computer History Museum.

Machine Learning

Tried *making a computer smart*, too hard!

Make a computer that can **learn** to be smart.



The Venn diagram of Artificial Intelligence, Machine Learning, Neural Networks and Deep Learning. Adapted from (Shang et al., 2025).

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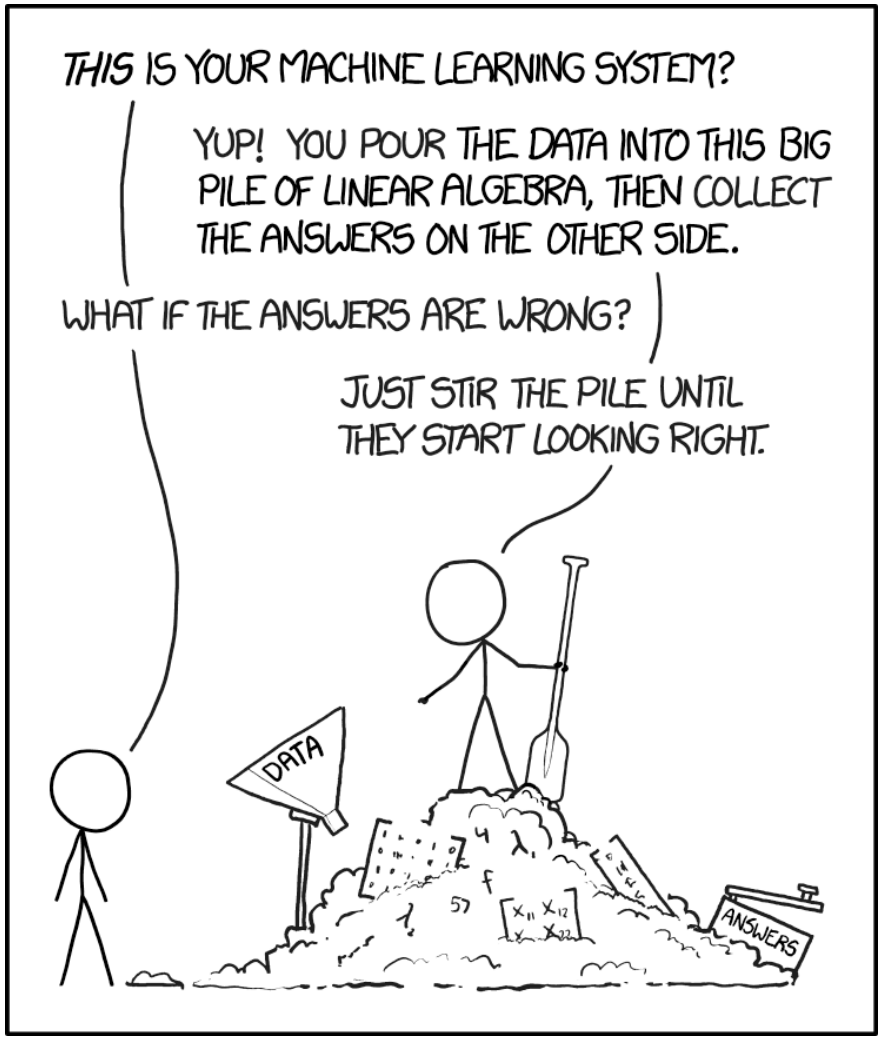
Definition

> "[Machine Learning is the] field of study that gives computers the ability to learn without being explicitly programmed"
> Arthur Samuel (1959)



Source: Randall Munroe (2017), xkcd #1838: Machine Learning.

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Image Classification I

What is this?

Options:

1. punching bag
2. goblet
3. red wine
4. hourglass
5. balloon

> **Note**
>
> Hover over the options to see AI's prediction (i.e. the probability of the photo being in that category).

Source: Wikipedia

Image Classification II

What is this?

Options:

1. sea urchin
2. porcupine
3. echidna
4. platypus
5. quill

Source: Wikipedia

Image Classification III

What is this?

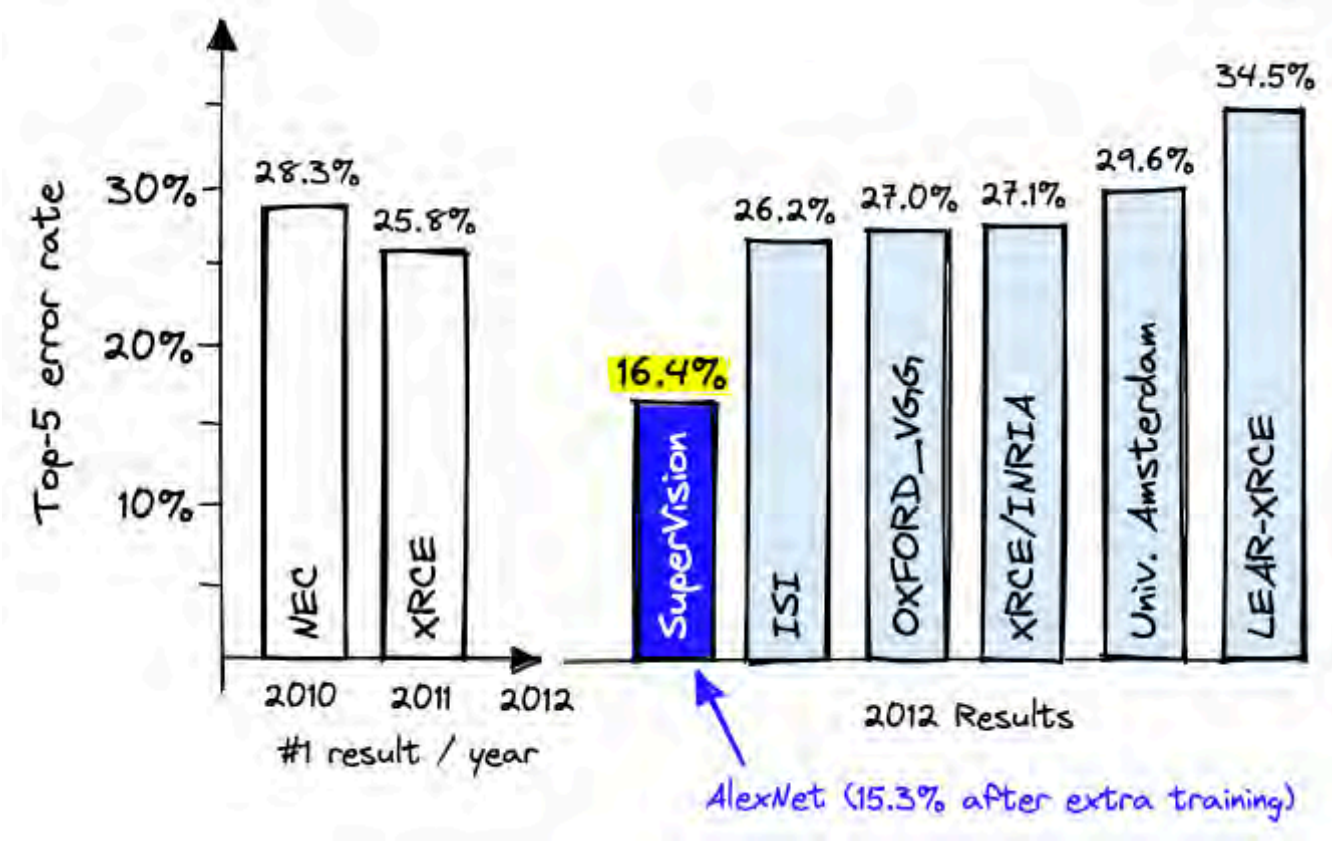
Options:

1. dingo
2. malinois
3. German shepherd
4. muzzle
5. kelpie

Source: Wikipedia

ImageNet Challenge

ImageNet and the *ImageNet Large Scale Visual Recognition Challenge (ILSVRC)*; originally 1,000 synsets.



AlexNet — a neural network developed by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton — won the ILSVRC 2012 challenge convincingly.

Source: James Briggs & Laura Carnevali, *AlexNet and ImageNet: The Birth of Deep Learning*, Embedding Methods for Image Search, Pinecone Blog

How were the images labelled?

The original 'mechanical turk' (1770)

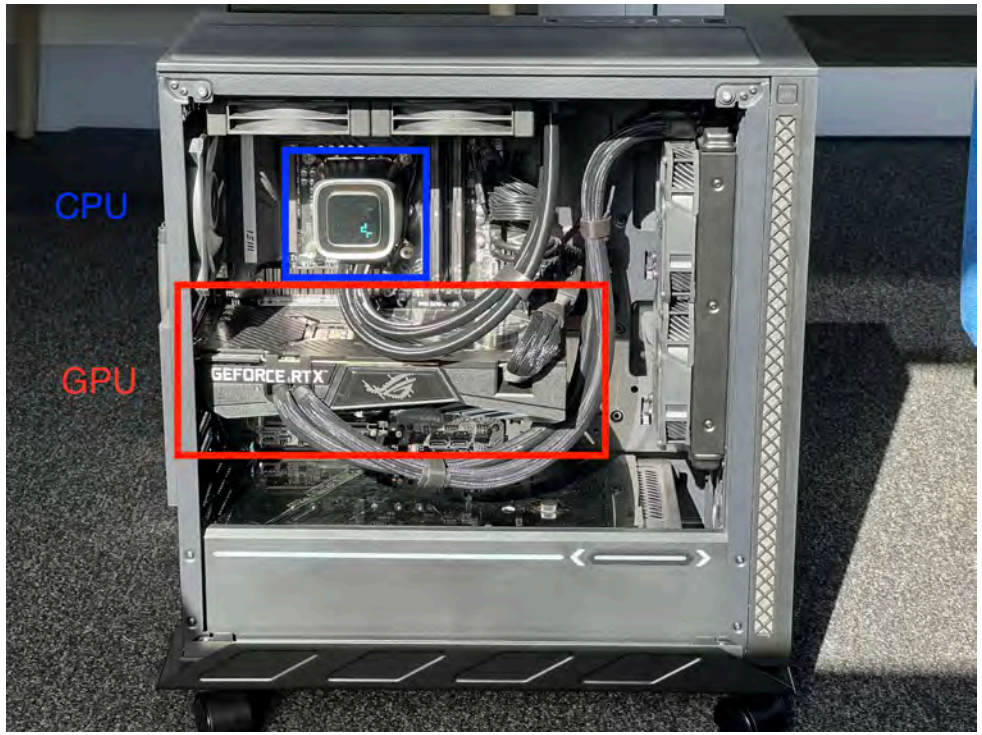
"Two years later, the first version of ImageNet was released with 12 million images structured and labeled in line with the WordNet ontology. If one person had annotated one image/minute and did nothing else in those two years (including sleeping or eating), it would have taken 22 years and 10 months.

To do this in under two years, Li turned to Amazon Mechanical Turk, a crowdsourcing platform where anyone can hire people from around the globe to perform tasks cost-effectively."

Sources: Editors of Encyclopaedia Britannica, The Mechanical Turk: AI Marvel or Parlor Trick?, and James Briggs & Laura Carnevali, *AlexNet and ImageNet: The Birth of Deep Learning*, Embedding Methods for Image Search, Pinecone Blog

Needed a graphics card

A graphics processing unit (GPU)



A PC with the GPU and CPU marked in red and blue.

> "**4.2. Training on multiple GPUs** A single GTX 580 GPU has only 3GB of memory, which limits the maximum size of the networks that can be trained on it. It turns out that 1.2 million training examples are enough to train networks which are too big to fit on one GPU. Therefore we spread the net across two GPUs."

Source: Krizhevsky, Sutskever and Hinton (2017), *ImageNet Classification with Deep Convolutional Neural Networks*, Communications of the ACM

Lee Sedol plays AlphaGo (2016)

Deep Blue was a win for AI, AlphaGo a win for ML.

Lee Sedol playing AlphaGo AI

I highly recommend this documentary about the event.

Source: Patrick House (2016), AlphaGo, Lee Sedol, and the Reassuring Future of Humans and Machines, New Yorker article.

Generative Adversarial Networks (2014)

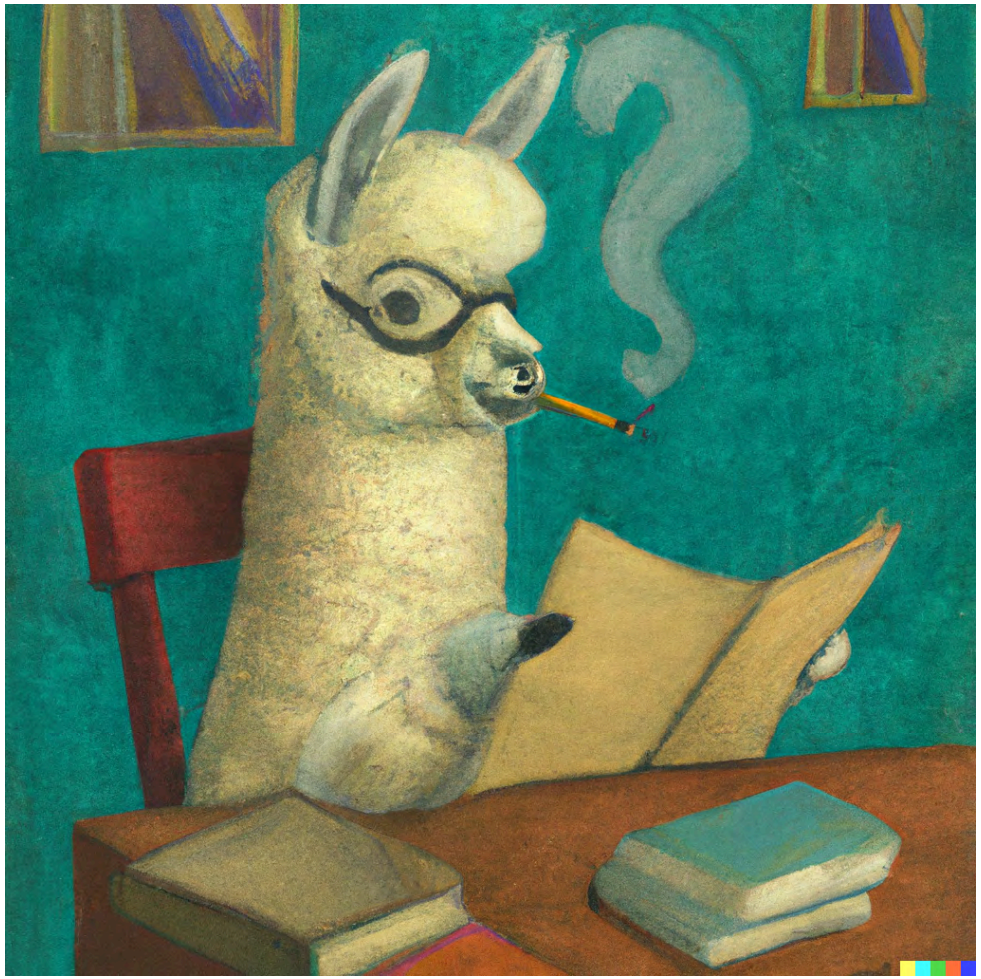
https://thispersondoesnotexist.com/

A GAN-generated face

A GAN-generated face

Diffusion models

Painting of avocado skating while wearing a hoodie



A surrealist painting of an alpaca studying for an exam

Source: Dall-E 2 images, prompts by ACTL3143 students in 2022.

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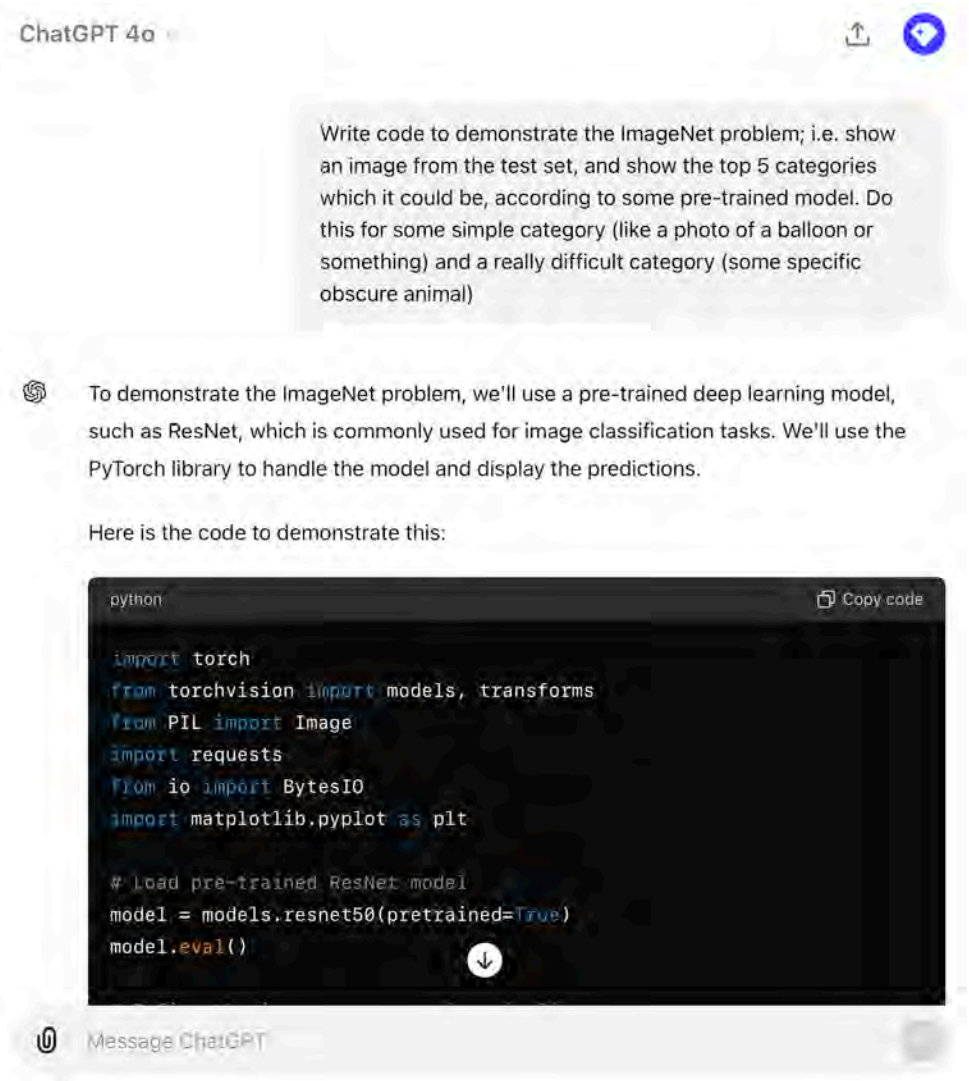
GPT



Homework Get ChatGPT to:

- generate images
- translate code
- explain code
- run code
- analyse a dataset
- critique code
- critique writing
- voice chat with you

Compare to Copilot.

AI predictions in the classification demo were from GPT code.

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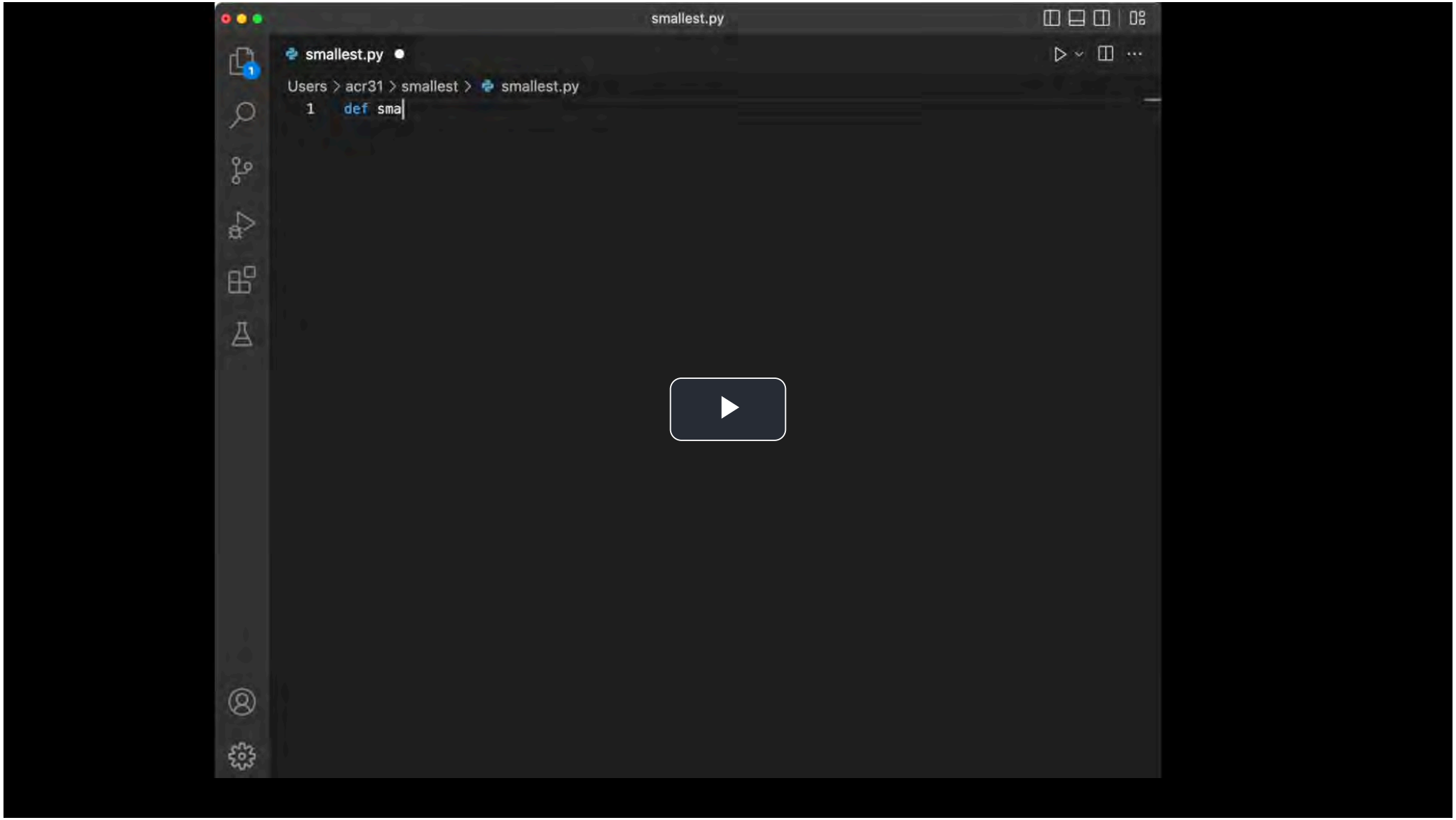
Code generation (GitHub Copilot)



Source: GitHub Blog

Students get extra Copilot for free

Use a free trial then sign up for free education account

Homework It's a slow process, so get this going early.

A student post from last year:

> I strongly recommend taking a photo holding up your Academic Statement to your phone's front facing camera when getting verified for the student account on GitHub. No other method of taking/uploading photo proofs worked for me. Furthermore, I had to make sure the name on the statement matched my profile exactly and also had to put in a bio.
>
> Good luck with this potentially annoying process!

Source: GitHub Education for Students

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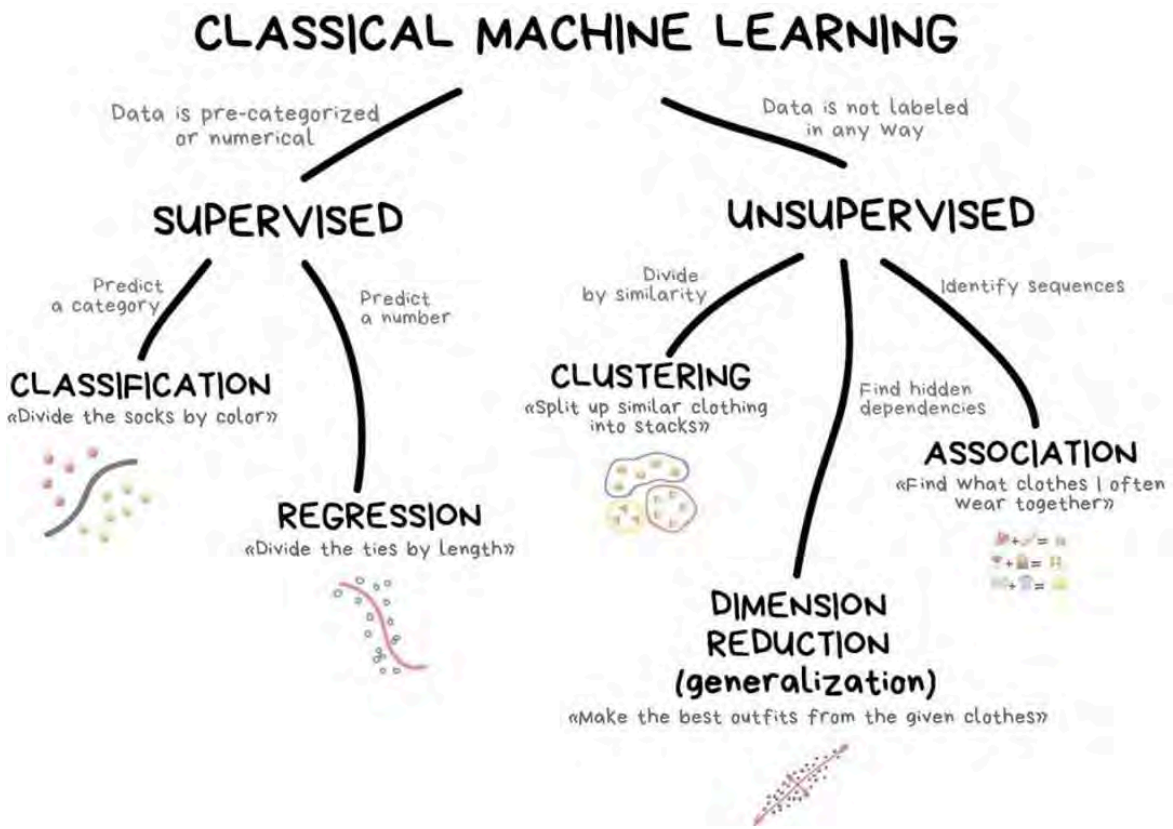
A taxonomy of problems



Machine learning categories in ACTL3142.

New ones:

- Reinforcement learning
- Semi-supervised learning
- Active learning

Source: Kaggle, Getting Started.

Supervised learning

The main focus of this course.

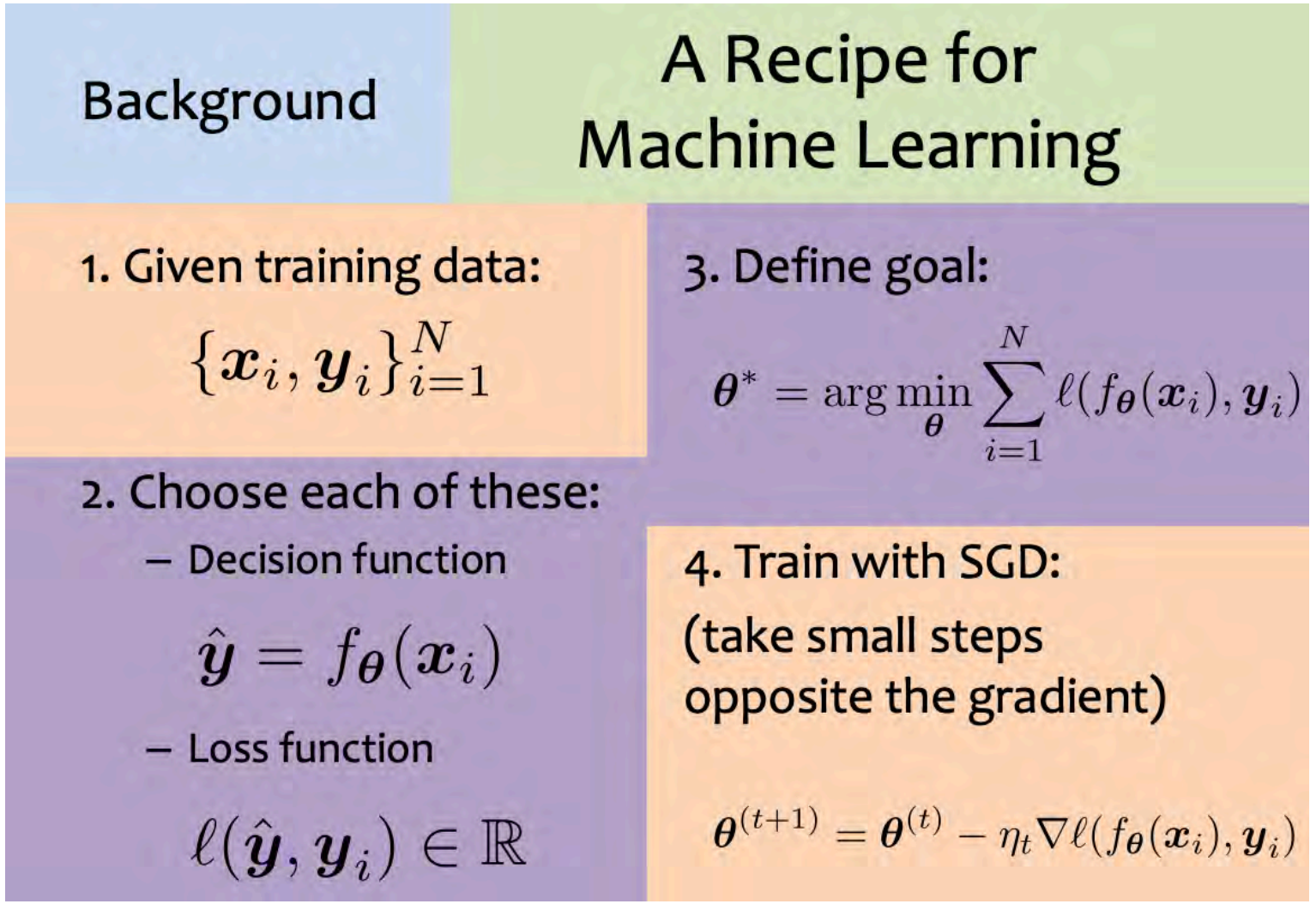
Regression

- Given policy $\hookrightarrow$ predict the rate of claims.
- Given policy $\hookrightarrow$ predict claim severity.
- Given a reserving triangle $\hookrightarrow$ predict future claims.

Classification

- Given a claim $\hookrightarrow$ classify as fraudulent or not.
- Given a customer $\hookrightarrow$ predict customer retention patterns.

Supervised learning: mathematically

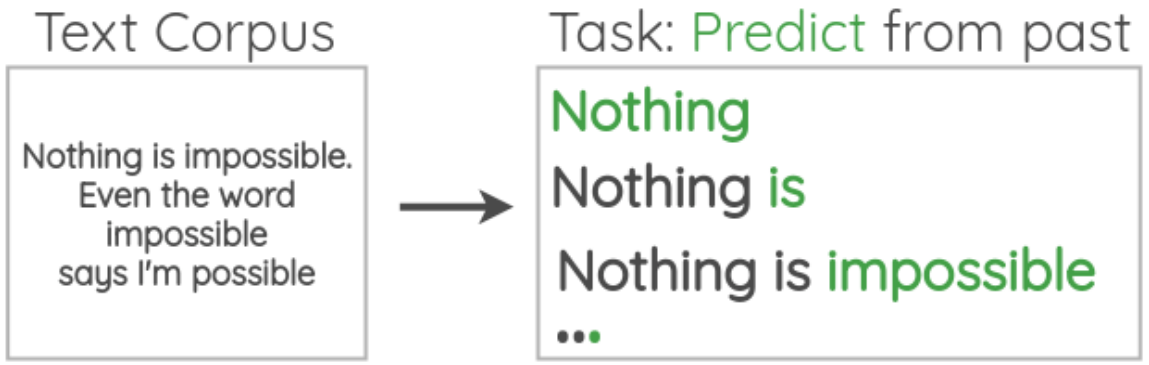


A recipe for supervised learning.

Source: Matthew Gormley (2021), Introduction to Machine Learning Lecture Slides, Slide 67.

Self-supervised learning

Data which 'labels itself'. Example: language model.

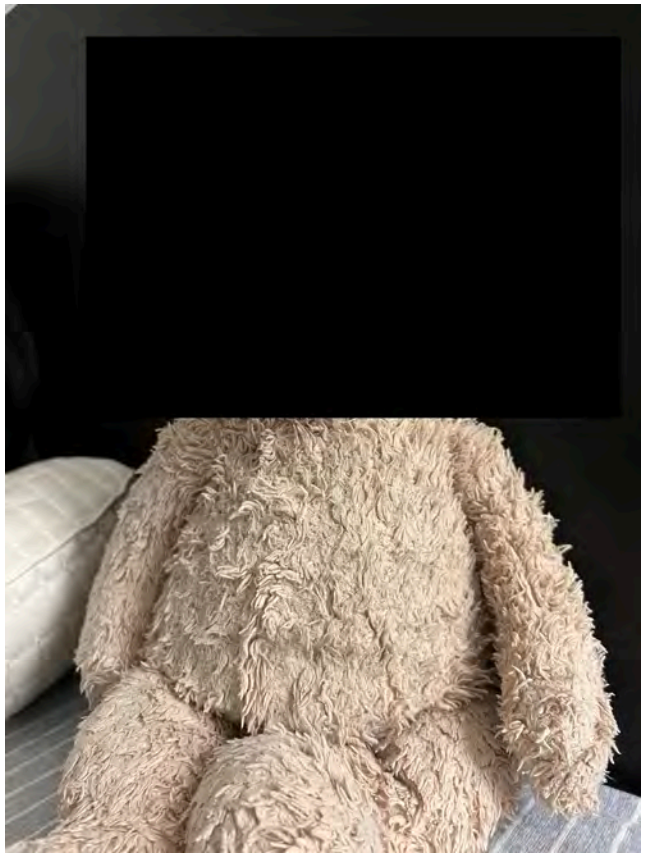


'Autoregressive' (e.g. GPT) versus 'masked' model (e.g. BERT).

Source: Amit Chaudhary (2020), Self Supervised Representation Learning in NLP.

Example: image inpainting

Original image



Randomly remove a part

Try to fill it in from context

Other examples: image super-resolution, denoising images.

See Liu et al. (2018), Image Inpainting for Irregular Holes using Partial Convolutions.

Example: Deoldify images #1

A deoldified version of the famous “Migrant Mother” photograph.

Source: Deoldify package.

Example: Deoldify images #2

A deoldified Golden Gate Bridge under construction.

Source: Deoldify package.

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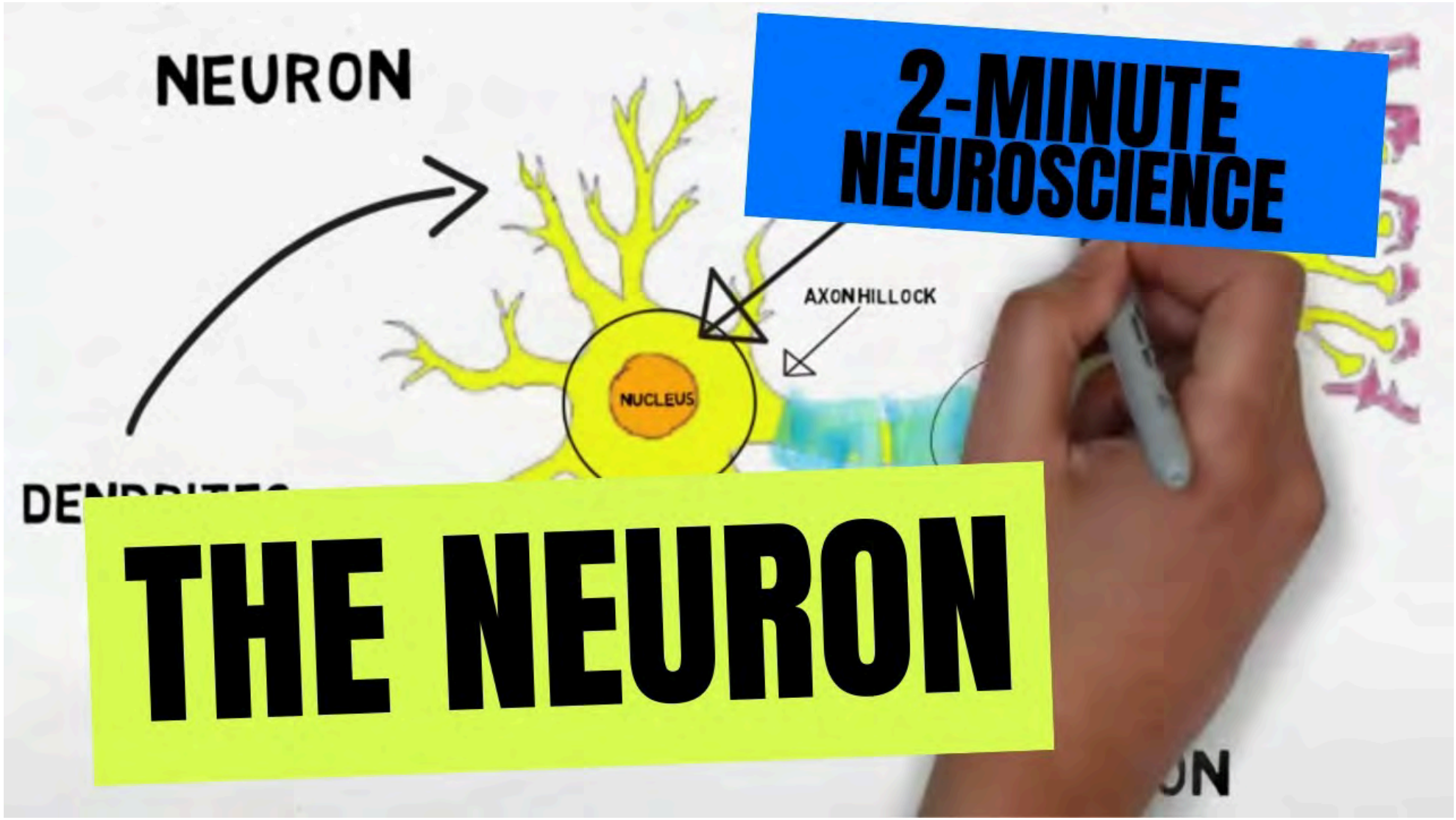
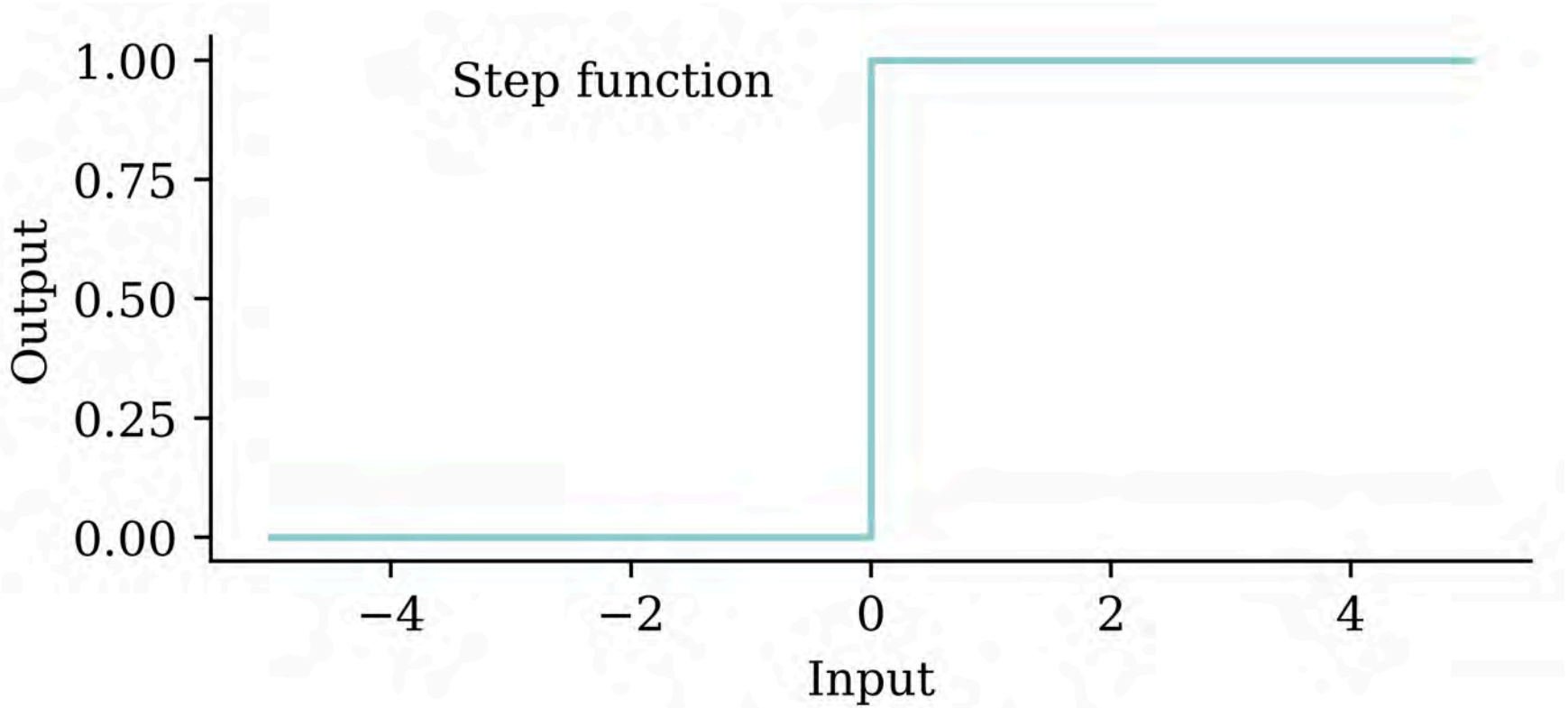
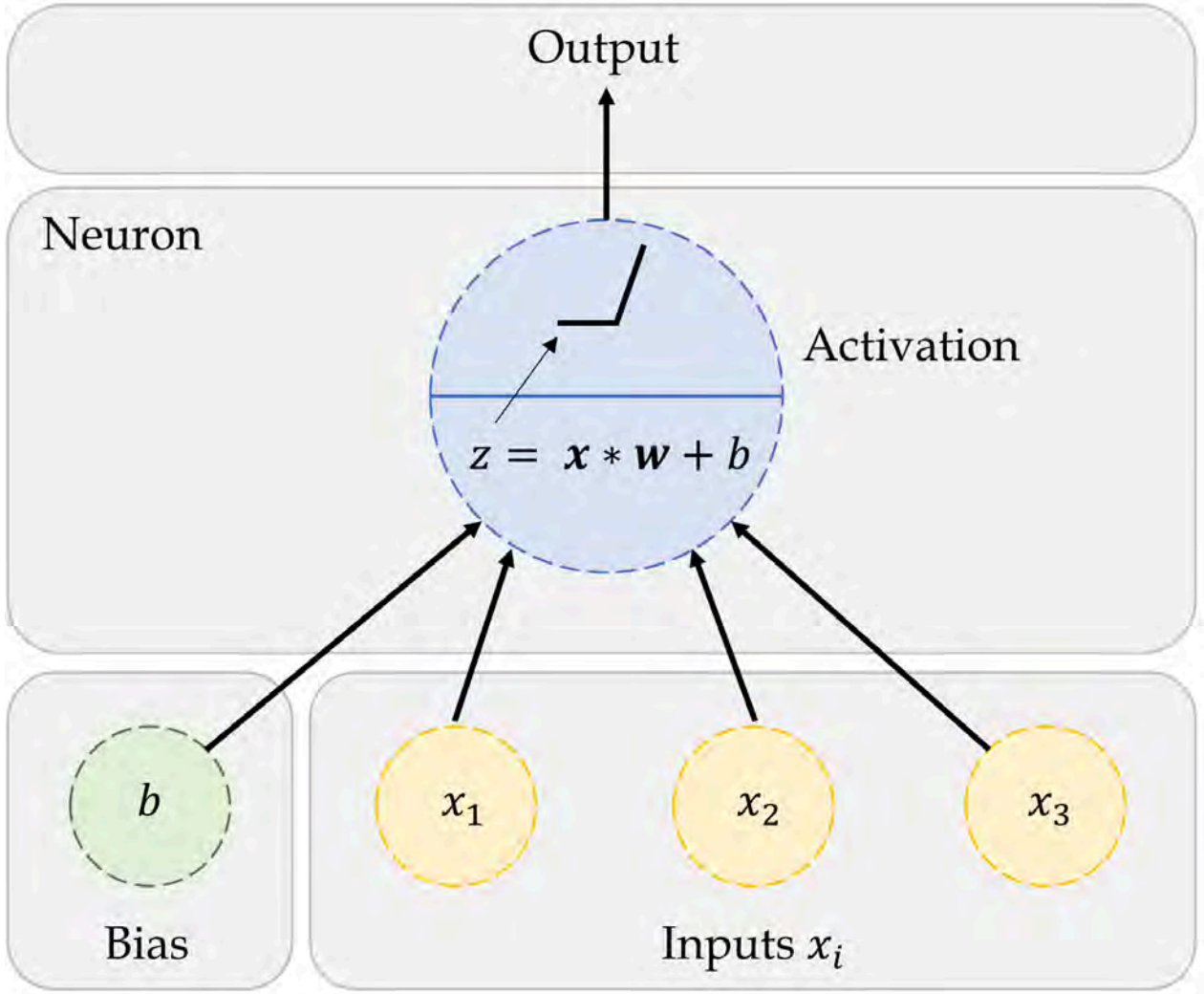
How do real neurons work?



A neuron ‘firing’



An artificial neuron



A neuron in a neural network with a ReLU activation.

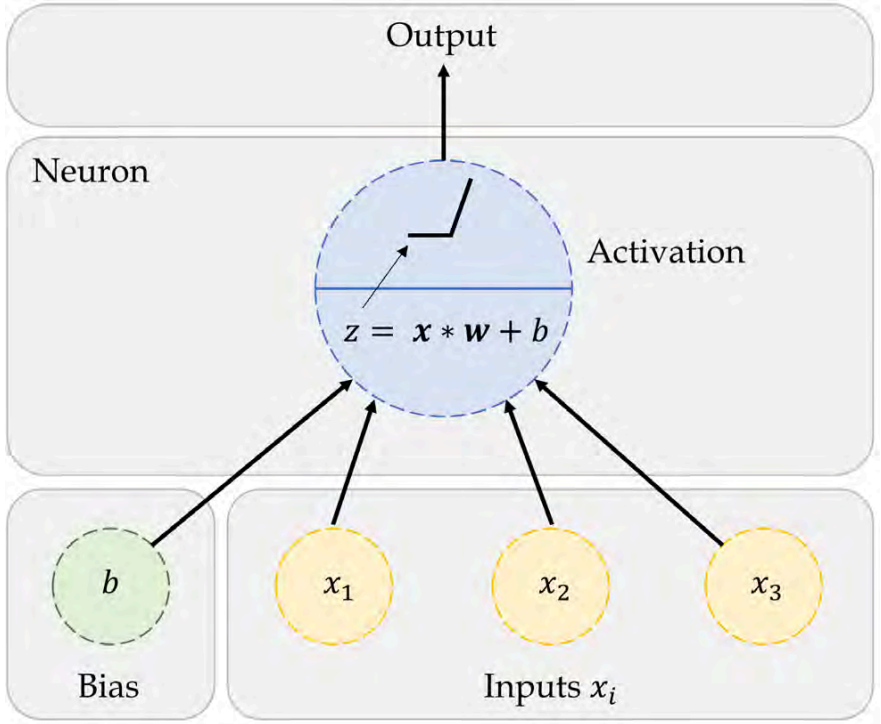
Source: Marcus Lautier (2022).

One neuron

$$
\begin{aligned}
z &= x_1 \times w_1 + \\
&\quad x_2 \times w_2 + \\
&\quad x_3 \times w_3.
\end{aligned}
$$

$$
a = \begin{cases} z & \text{if } z > 0 \\ 0 & \text{if } z \leq 0 \end{cases}
$$

Here, x_1, x_2, x_3 are just some fixed data.



A neuron in a neural network with a ReLU activation.

The weights w_1, w_2, w_3 should be 'learned'.

Source: Marcus Lautier (2022).

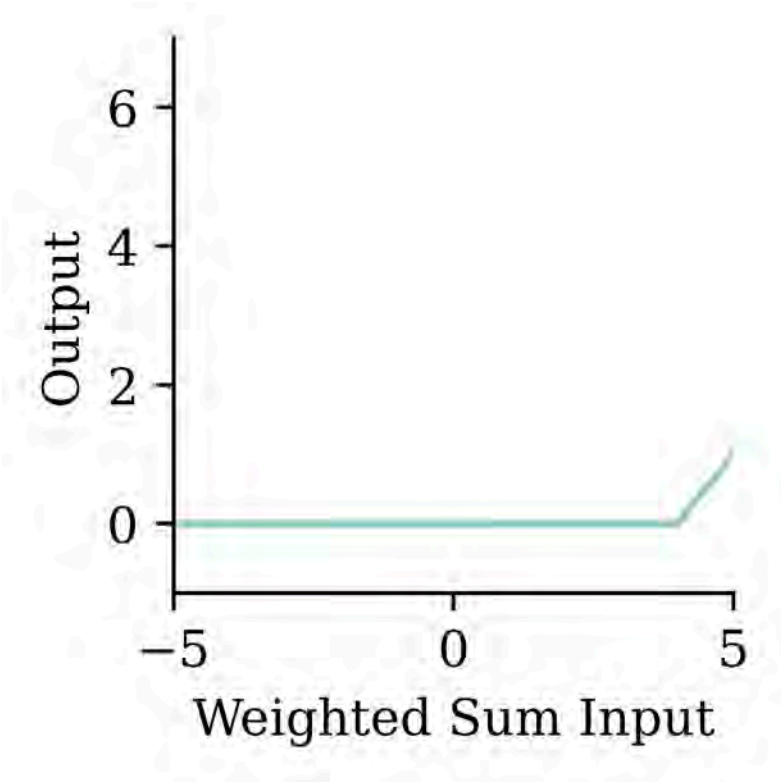
One neuron with bias

$$
\begin{aligned}
z &= x_1 \times w_1 + \\
&\quad x_2 \times w_2 + \\
&\quad x_3 \times w_3 + b.
\end{aligned}
$$

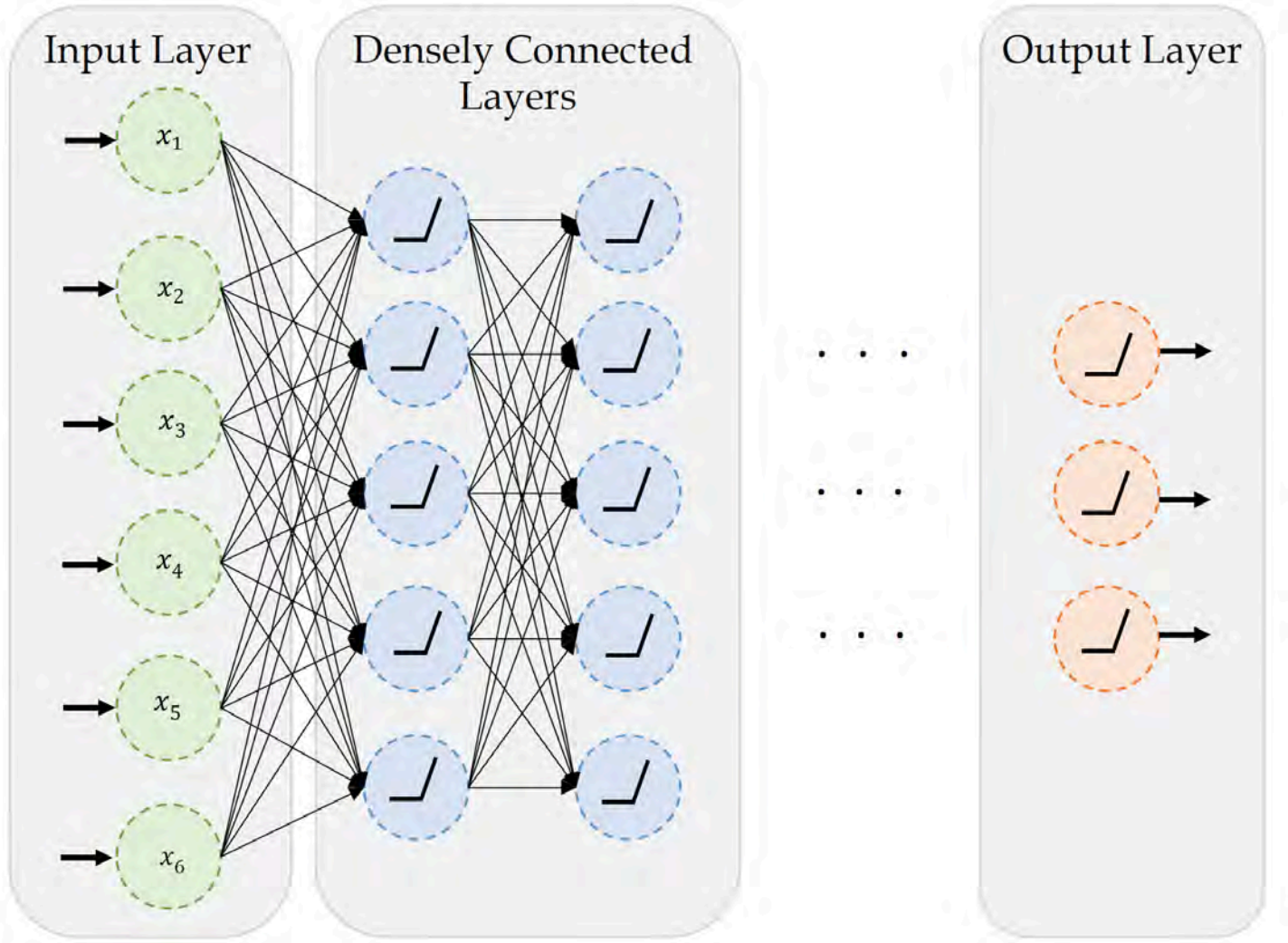
$$
a = \begin{cases} z & \text{if } z > 0 \\ 0 & \text{if } z \leq 0 \end{cases}
$$

The weights w_1, w_2, w_3 and bias b should be 'learned'.

Bias = -4 | 0 | 4



A basic neural network



A basic fully-connected/dense network.

Source: Marcus Lautier (2022).

Step-function activation

Perceptrons

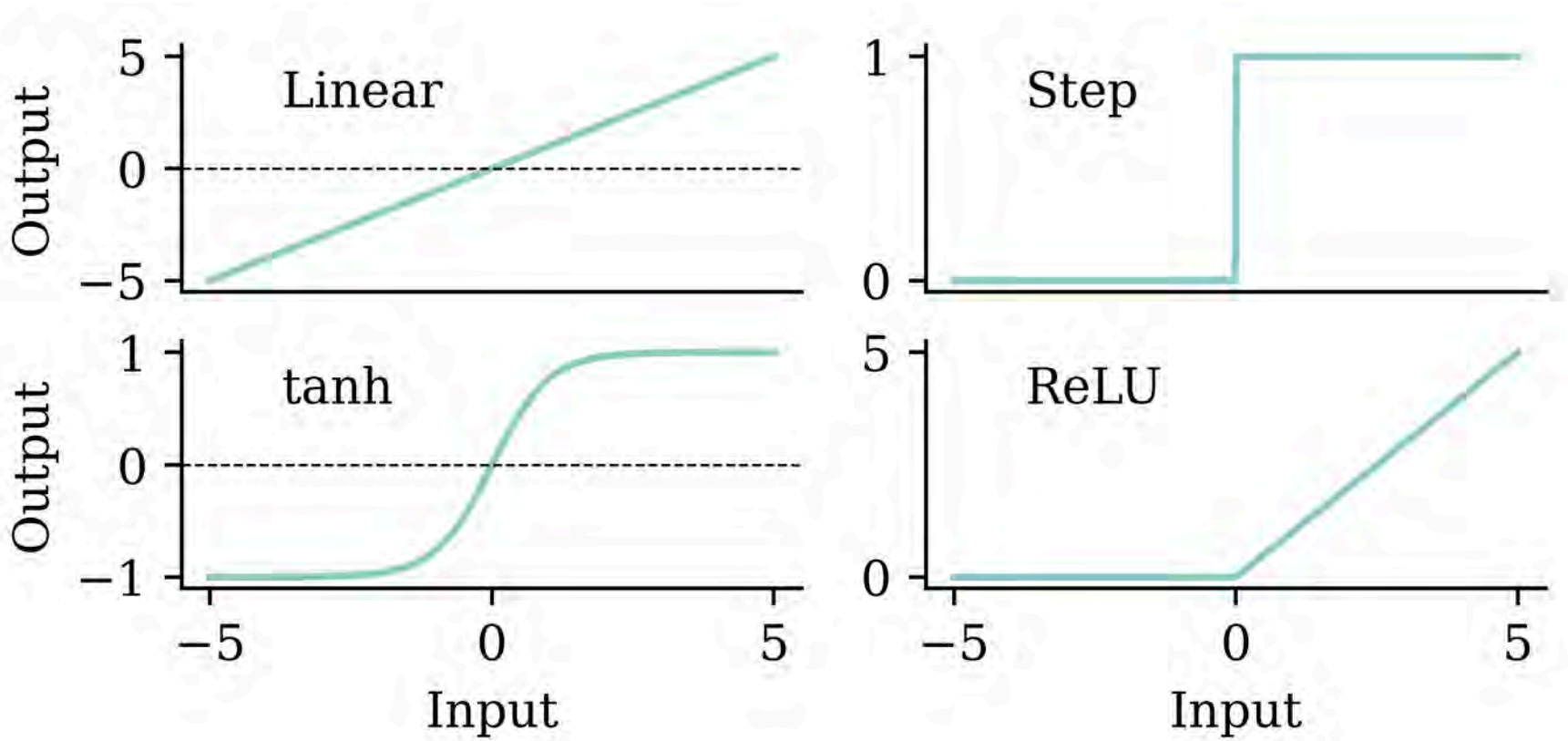
Brains and computers are binary, so make a perceptron with binary data. Seemed reasonable, impossible to train.

Modern neural network

Replace binary state with continuous state. Still rather slow to train.

> **Note**
>
> It's a neur**al** network made of neur**on**s, not a "neuron network".

Try different activation functions

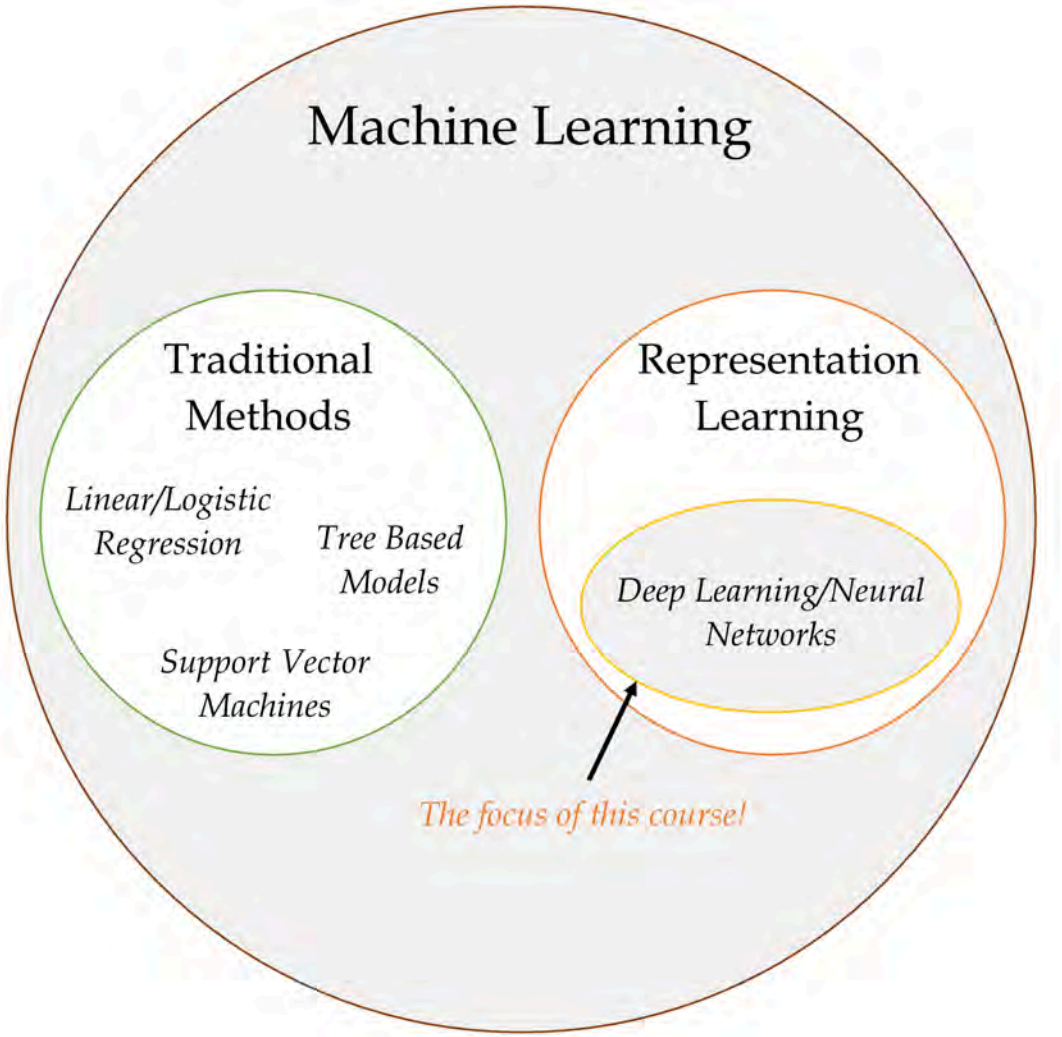


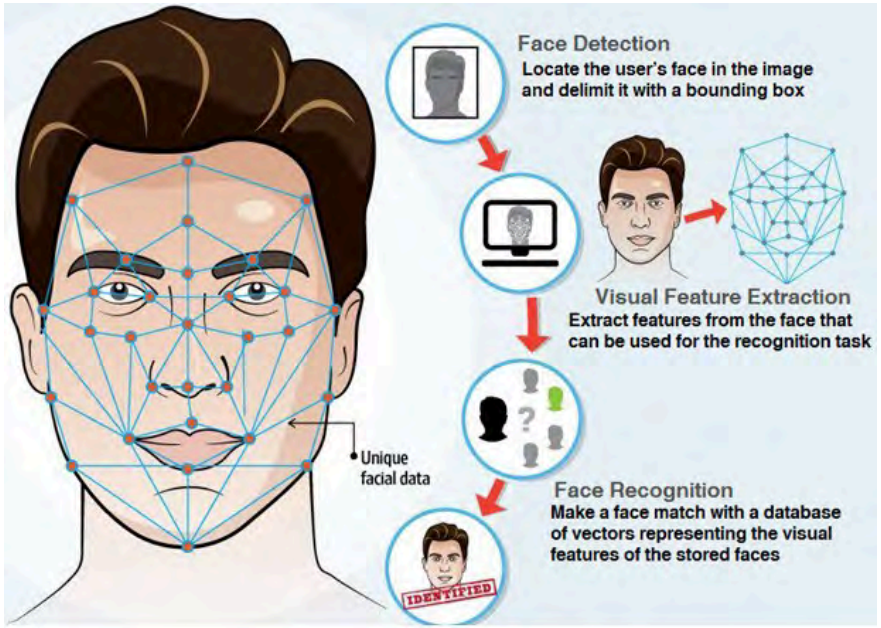
Flexible

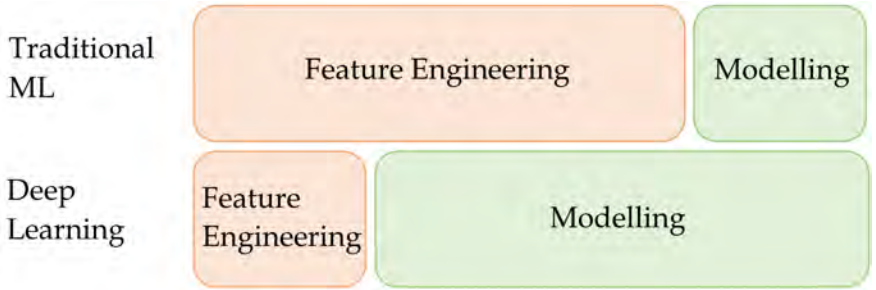
> One can show that an MLP is a **universal approximator**, meaning it can model any suitably smooth function, given enough hidden units, to any desired level of accuracy (Hornik 1991). One can either make the model be “wide” or “deep”; the latter has some advantages...

Source: Murphy (2012), Machine Learning: A Probabilistic Perspective, 1st Ed, p. 566.

Feature engineering







Sources: Marcus Lautier (2022) & Fenjiro (2019), *Face Id: Deep Learning for Face Recognition*, Medium.

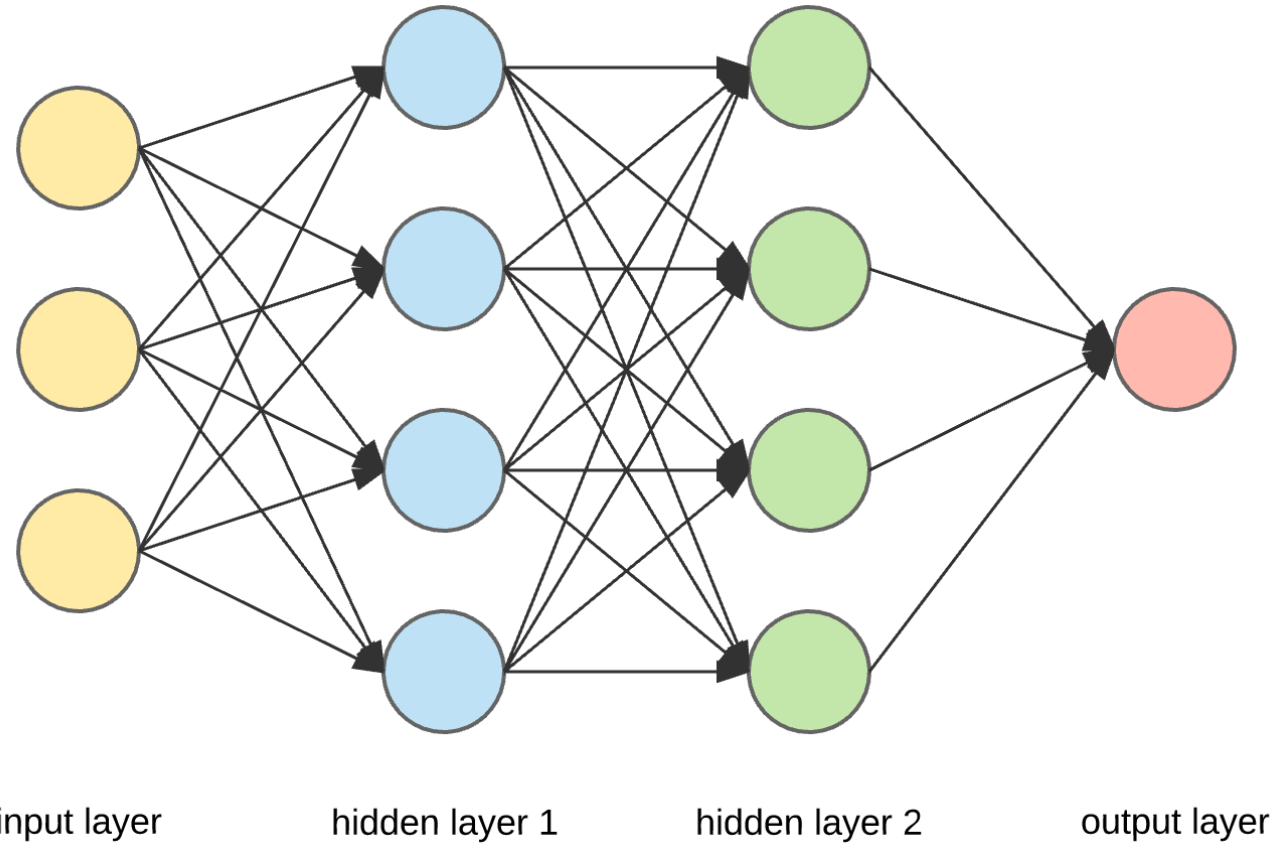
Doesn't mean deep learning is always the best option!

Quiz

In this ANN, how many of the following are there:

- features,
- targets,
- weights,
- biases, and
- parameters?

What is the depth?



An artificial neural network.

Source: Dertat (2017), *Applied Deep Learning - Part 1: Artificial Neural Networks*, Medium.

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Imports needed for this demo

```python
import random
from pathlib import Path

import numpy as np

from sklearn.datasets import fetch_california_housing
from sklearn.model_selection import train_test_split

from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import StandardScaler, MinMaxScaler

from keras.models import Sequential
from keras.layers import Dense, Input

from keras.callbacks import EarlyStopping
from keras.callbacks import ModelCheckpoint
```

Data science always starts with the data!

> The target variable is the median house value for California districts, expressed in $100,000's. This dataset was derived from the 1990 U.S. census, using one row per census block group. A block group is the smallest geographical unit for which the U.S. Census Bureau publishes sample data (a block group typically has a population of 600 to 3,000 people).

Dall-E's rendition of this dataset.

Source: Scikit-learn documentation.

Columns

- `MedInc` median income in block group
- `HouseAge` median house age in block group
- `AveRooms` average number of rooms per household
- `AveBedrms` average # of bedrooms per household
- `Population` block group population
- `AveOccup` average number of household members
- `Latitude` block group latitude
- `Longitude` block group longitude
- `MedHouseVal` median house value (**target**)

Source: Scikit-learn documentation.

Import the data

```
features, target = fetch_california_housing(as_frame=True, return_X_y=True)
features
```

	MedInc	HouseAge	AveRooms	AveBedrms	Population	AveOccup	Latitude	Longitude
0	8.3252	41.0	6.984127	1.023810	322.0	2.555556	37.88	-122.23
1	8.3014	21.0	6.238137	0.971880	2401.0	2.109842	37.86	-122.22
2	7.2574	52.0	8.288136	1.073446	496.0	2.802260	37.85	-122.24
...	...	...	...	...	...	...	...	...
20637	1.7000	17.0	5.205543	1.120092	1007.0	2.325635	39.43	-121.22
20638	1.8672	18.0	5.329513	1.171920	741.0	2.123209	39.43	-121.32
20639	2.3886	16.0	5.254717	1.162264	1387.0	2.616981	39.37	-121.24

20640 rows × 8 columns

Train/validation/test split

```
X_main, X_test, y_main, y_test = train_test_split(
    features, target, test_size=0.2, random_state=1)
X_train, X_val, y_train, y_val = train_test_split(
    X_main, y_main, test_size=0.25, random_state=1)

num_features = features.shape[1]
print(X_train.shape, X_val.shape, X_test.shape)
```

```
(12384, 8) (4128, 8) (4128, 8)
```

Linear regression baseline

Refit the linear regression from earlier; we'll compare neural networks against this baseline.

```
lr = LinearRegression()
lr.fit(X_train, y_train)

mse_lr_train = mean_squared_error(y_train, lr.predict(X_train))
mse_lr_val = mean_squared_error(y_val, lr.predict(X_val))

mse_train = {"Linear Regression": mse_lr_train}
mse_val = {"Linear Regression": mse_lr_val}
```

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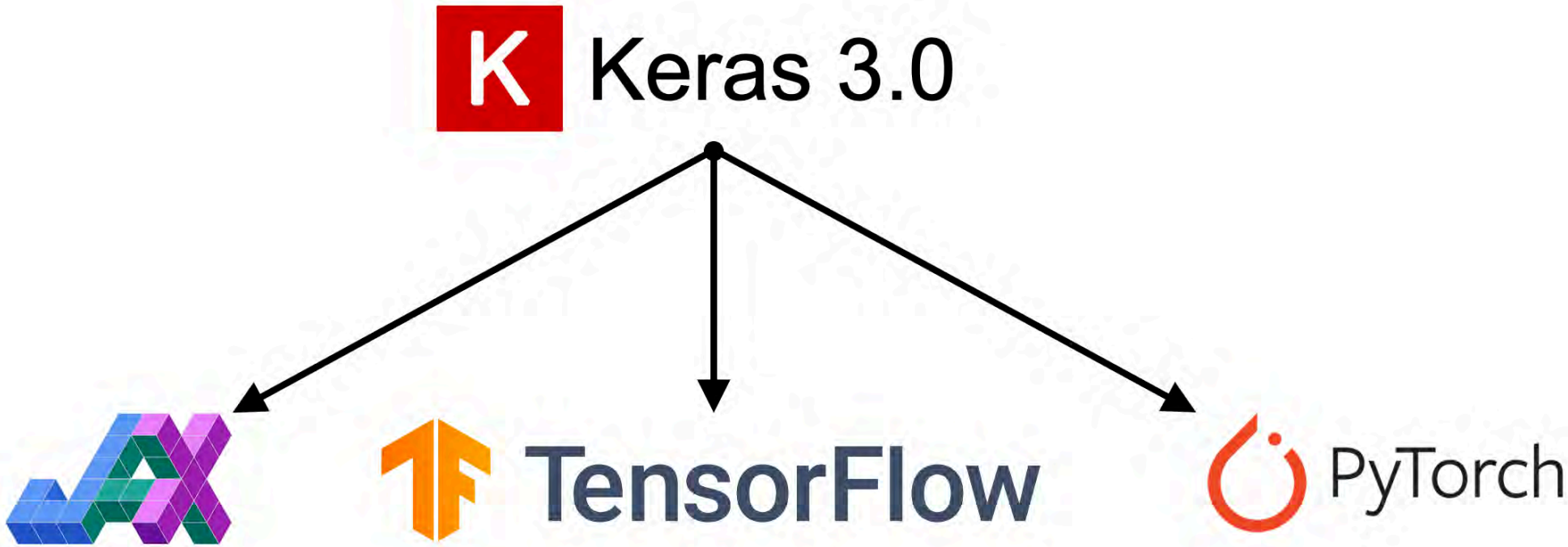
What are Keras and PyTorch?

Keras is a common way of specifying, training, and using neural networks. It gives a simple interface to *various backend* libraries, including PyTorch.



The Keras application programming interface (API)

Source: Melissa Renard (2025)

Create a Keras ANN model

Decide on the architecture: a simple fully-connected network with one hidden layer with 30 neurons.

Create the model:

```
model = Sequential(
    [Input((num_features,)),
     Dense(30, activation="leaky_relu"),
     Dense(1, activation="leaky_relu")]
)
```

Inspect the model

```
1 model.summary()
```

Model: "sequential"

Layer (type)	Output Shape	Param #
dense (Dense)	(None, 30)	270
dense_1 (Dense)	(None, 1)	31

Total params: 301 (1.18 KB)
Trainable params: 301 (1.18 KB)
Non-trainable params: 0 (0.00 B)

The model is initialised randomly

```
1 model = Sequential([Dense(30, activation="leaky_relu"), Dense(1, activation="leaky_relu")
2 model.predict(X_val.head(3), verbose=0)
```

```
array([[-139.05],
       [ -84.57],
       [  -5.82]], dtype=float32)
```

```
1 model = Sequential([Dense(30, activation="leaky_relu"), Dense(1, activation="leaky_relu")
2 model.predict(X_val.head(3), verbose=0)
```

```
array([[-108.21],
       [ -64.74],
       [  -7.1 ]], dtype=float32)
```

Controlling the randomness

```
random.seed(123)

model = Sequential([Dense(30, activation="leaky_relu"), Dense(1, activation="leaky_relu")])

display(model.predict(X_val.head(3), verbose=0))

random.seed(123)
model = Sequential([Dense(30, activation="leaky_relu"), Dense(1, activation="leaky_relu")])

display(model.predict(X_val.head(3), verbose=0))
```

```
array([[-81.4 ],
       [-48.06],
       [ -2.77]], dtype=float32)
```

```
array([[-81.4 ],
       [-48.06],
       [ -2.77]], dtype=float32)
```

Fit the model

```
random.seed(123)

model = Sequential([
    Dense(30, activation="leaky_relu"),
    Dense(1, activation="leaky_relu")
])

model.compile("adam", "mse")
%time hist = model.fit(X_train, y_train, epochs=5, verbose=False)
hist.history["loss"]
```

```
CPU times: user 3.39 s, sys: 113 ms, total: 3.5 s
Wall time: 3.45 s
```

```
[63.02413558959961,
 3.4991047382354736,
 3.3900036811828613,
 2.1773459911346436,
 2.335667848587036]
```

Make predictions

```
1 y_pred = model.predict(X_train[:3], verbose=0)
2 y_pred
```

```
array([[ 0.29],
       [-0.91],
       [-0.17]], dtype=float32)
```

Note

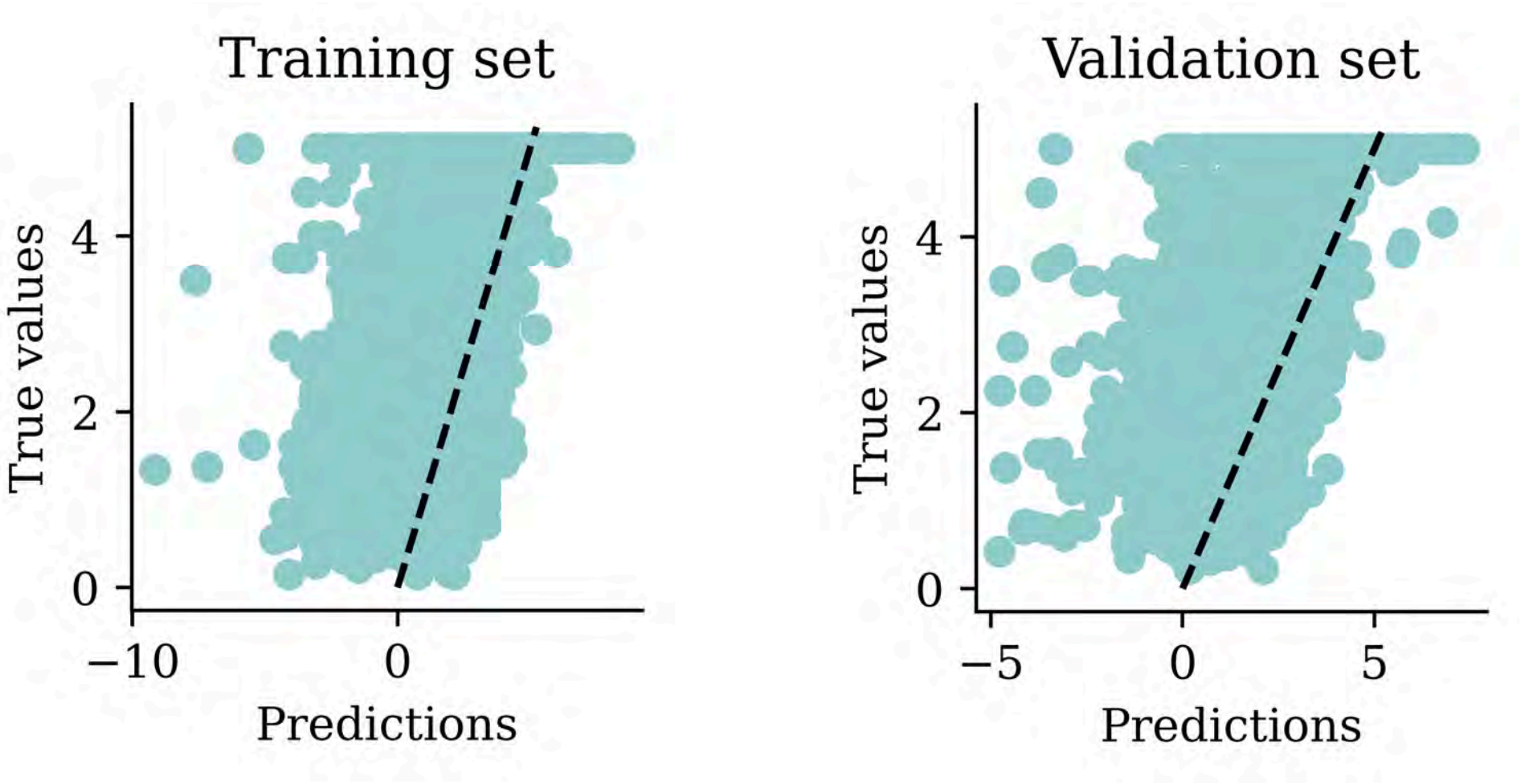
The `.predict` gives us a 'matrix' not a 'vector'. Calling `.flatten()` will convert it to a 'vector'.

```
1 print(f"Original shape: {y_pred.shape}")
2 y_pred = y_pred.flatten()
3 print(f"Flattened shape: {y_pred.shape}")
4 y_pred
```

```
Original shape: (3, 1)
Flattened shape: (3,)
```

```
array([ 0.29, -0.91, -0.17], dtype=float32)
```

Plot the predictions



Assess the model

```
y_pred = model.predict(X_val, verbose=0)
mean_squared_error(y_val, y_pred)
```

```
2.845539574957286
```

```
mse_train["Basic ANN"] = mean_squared_error(
    y_train, model.predict(X_train, verbose=0)
)
mse_val["Basic ANN"] = mean_squared_error(y_val, model.predict(X_val, verbose=0))
```

Some predictions are negative:

```
y_pred = model.predict(X_val, verbose=0)
y_pred.min(), y_pred.max()
```

```
(np.float32(-4.7767005), np.float32(7.326745))
```

```
y_val.min(), y_val.max()
```

```
(np.float64(0.225), np.float64(5.00001))
```

Lecture Outline

- Artificial Intelligence
- Deep Learning Successes (Images)
- Deep Learning Successes (Text)
- Classifying Machine Learning Tasks
- Neural Networks
- California House Price Prediction
- Our First Neural Network
- **Force positive predictions**
- Preprocessing
- Early Stopping

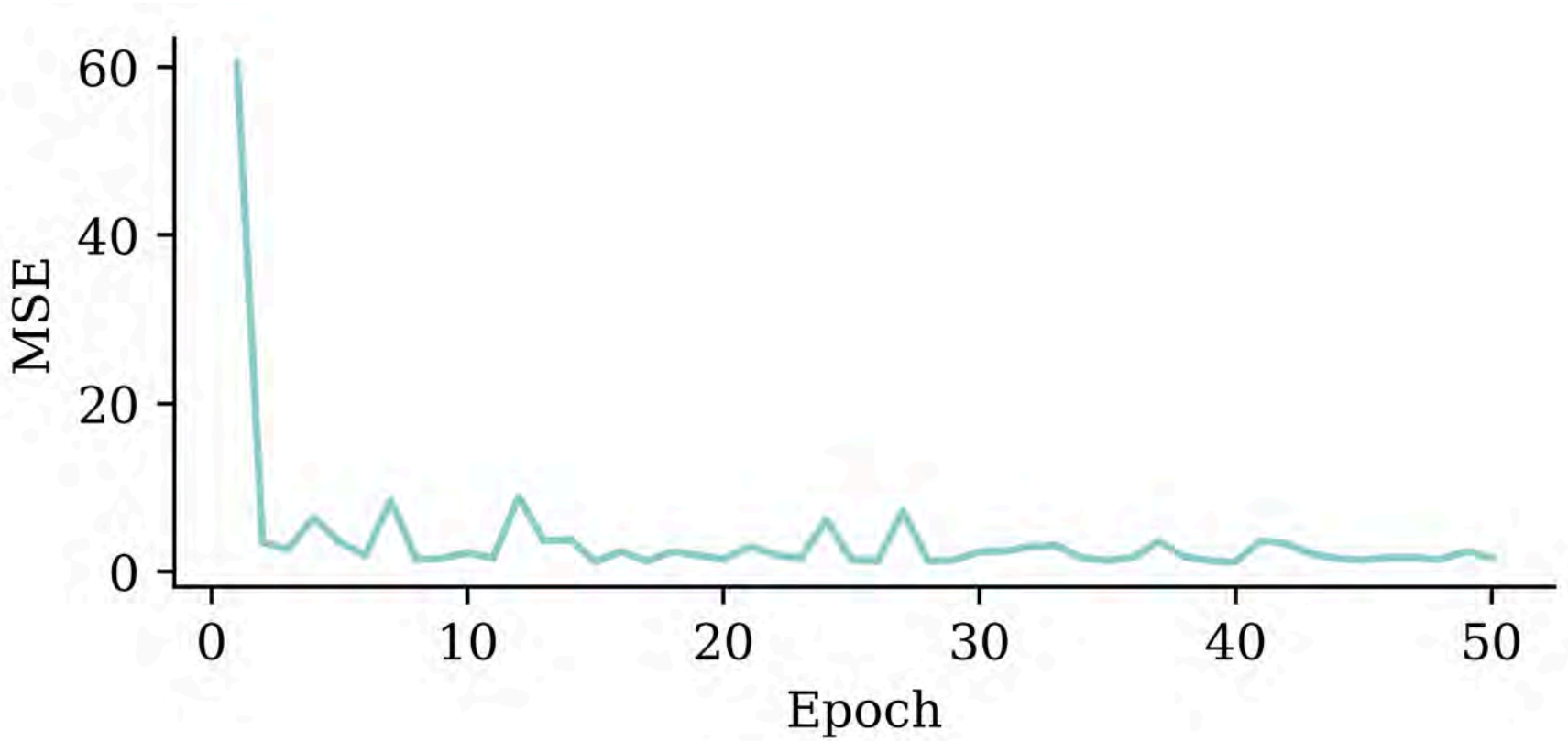
Try running for longer

```
random.seed(123)

model = Sequential([
    Dense(30, activation="leaky_relu"),
    Dense(1, activation="leaky_relu")
])

model.compile("adam", "mse")

%time hist = model.fit(X_train, y_train, epochs=50, verbose=False)
```

```
CPU times: user 33.6 s, sys: 840 ms, total: 34.4 s
Wall time: 33.8 s
```

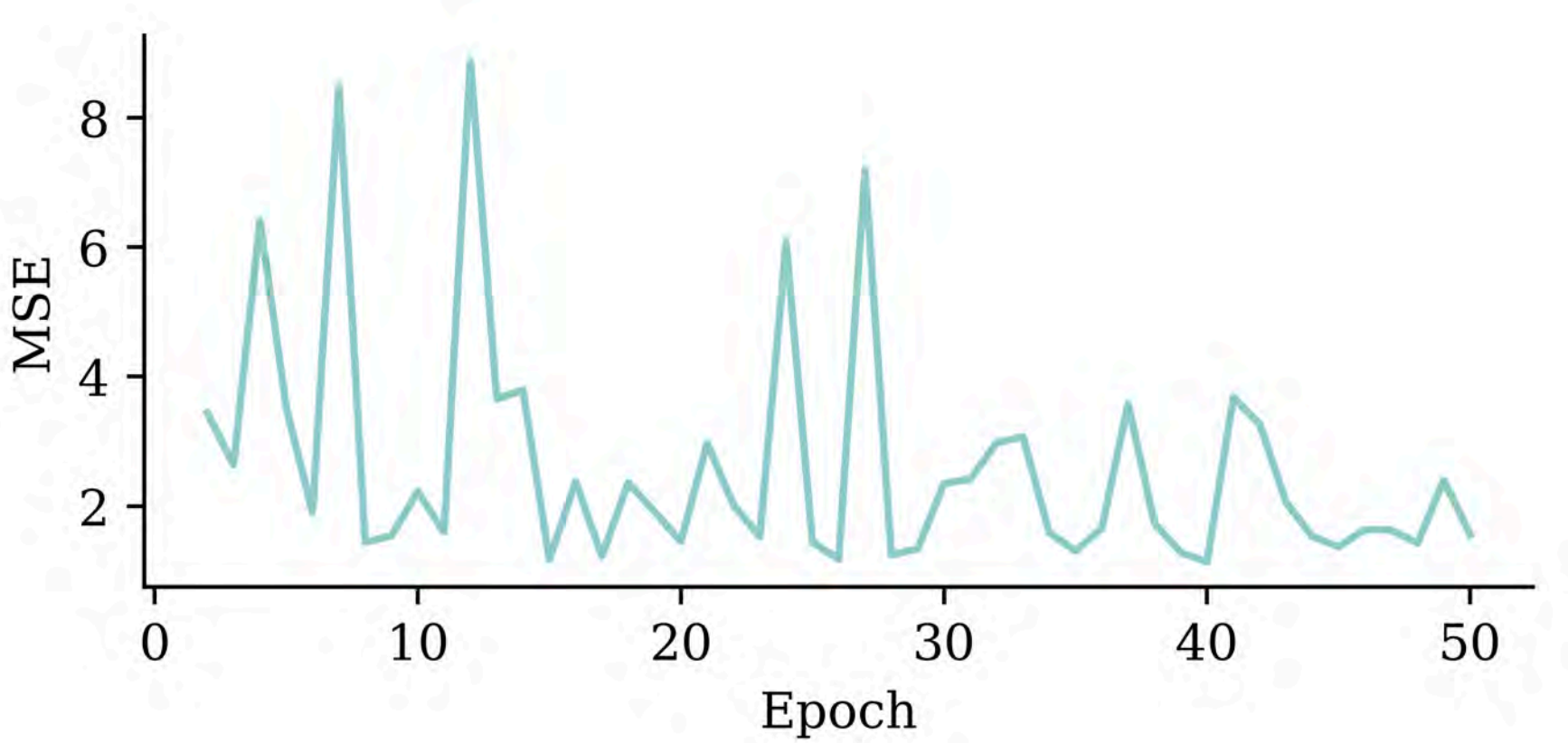
Loss curve

```
1 plt.plot(range(1, 51), hist.history["loss"])
2 plt.xlabel("Epoch")
3 plt.ylabel("MSE");
```



Loss curve

```
1 plt.plot(range(2, 51), hist.history["loss"][1:])
2 plt.xlabel("Epoch")
3 plt.ylabel("MSE");
```



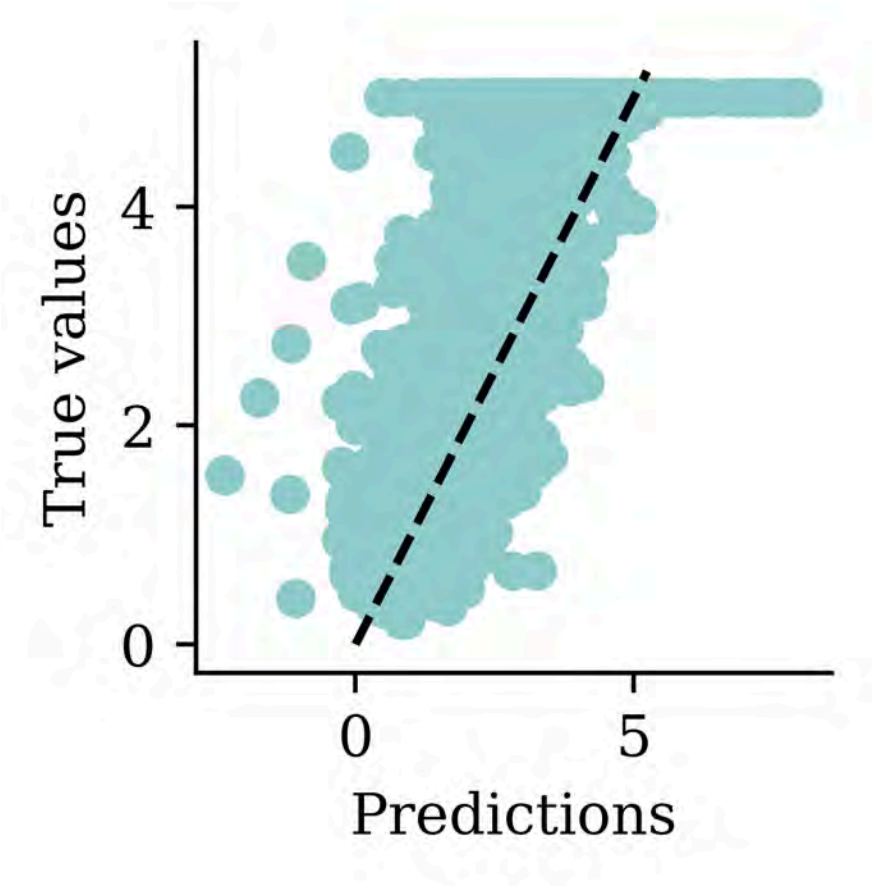
Predictions

```
y_pred = model.predict(X_val, verbose=0)
print(f"Min prediction: {y_pred.min():.2f}")
print(f"Max prediction: {y_pred.max():.2f}")
```

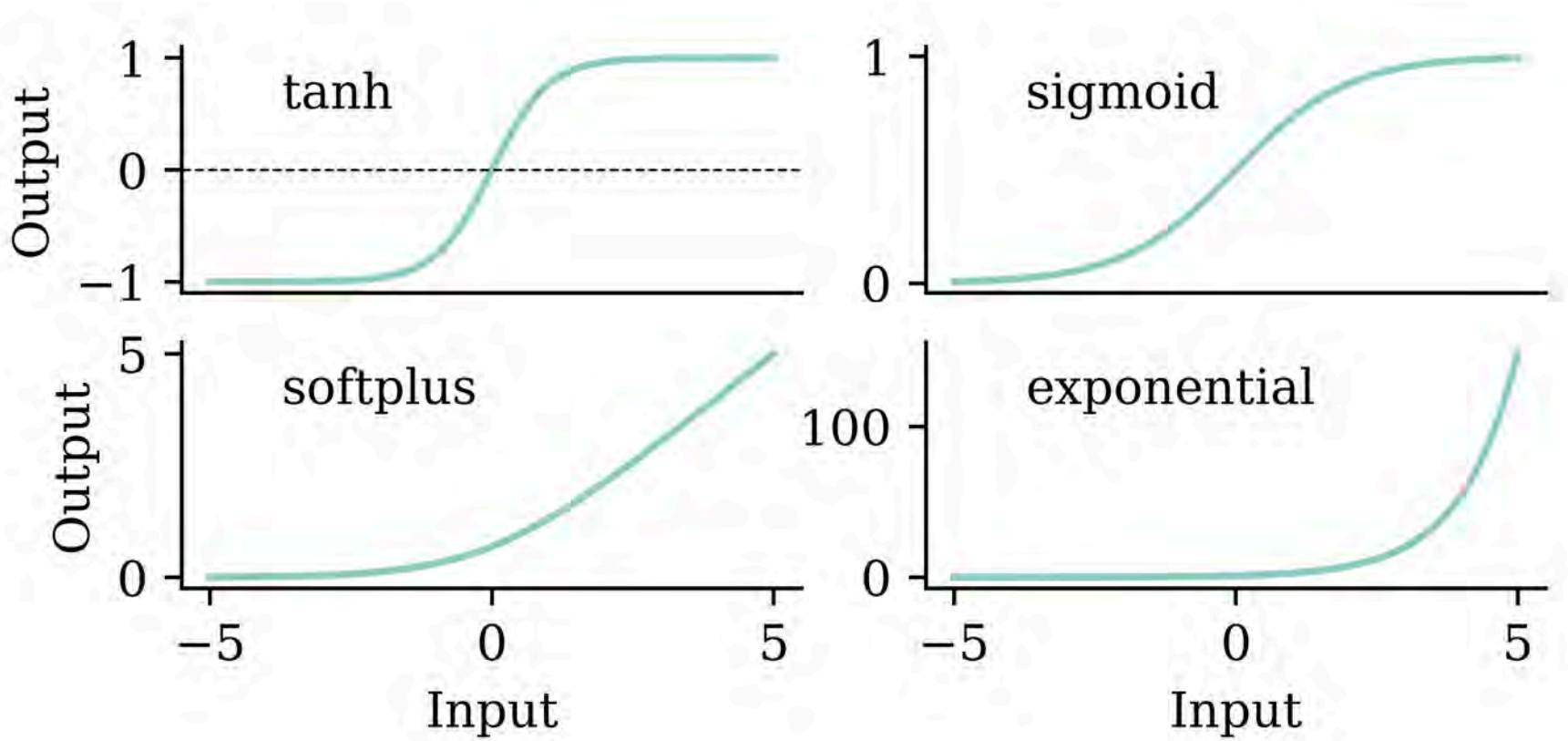
```
Min prediction: -2.35
Max prediction: 8.03
```

```
plt.scatter(y_pred, y_val)
plt.xlabel("Predictions")
plt.ylabel("True values")
add_diagonal_line()
```

```
mse_train["Long run ANN"] = mean_squared_
    y_train, model.predict(X_train, verbo
)
mse_val["Long run ANN"] = mean_squared_er
```



Try different activation functions

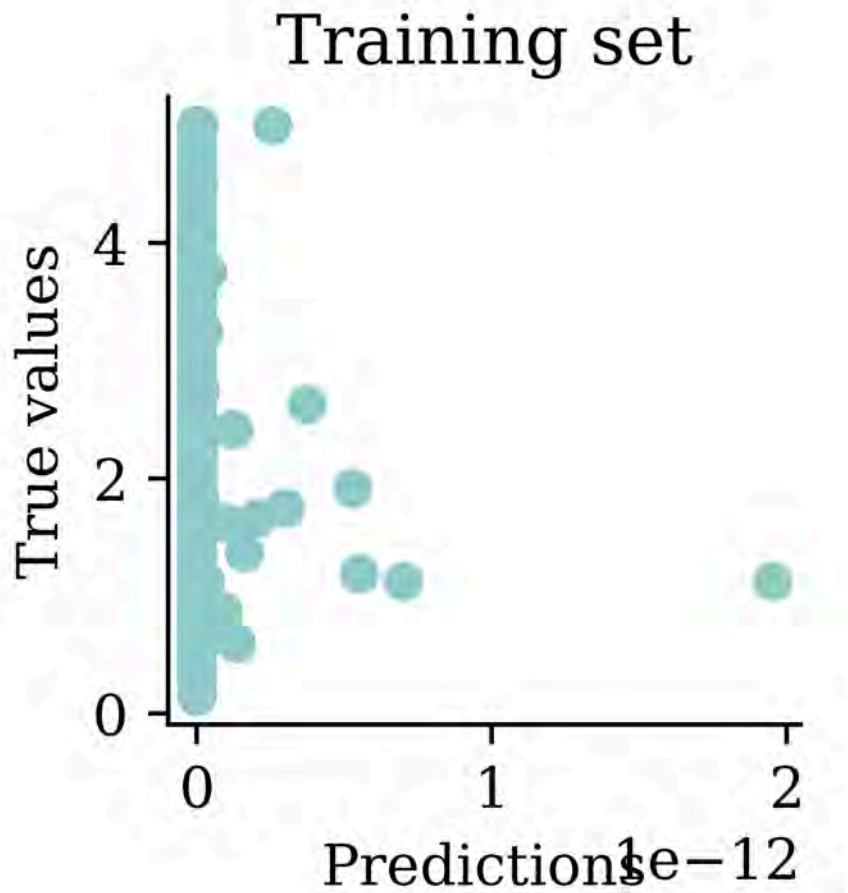


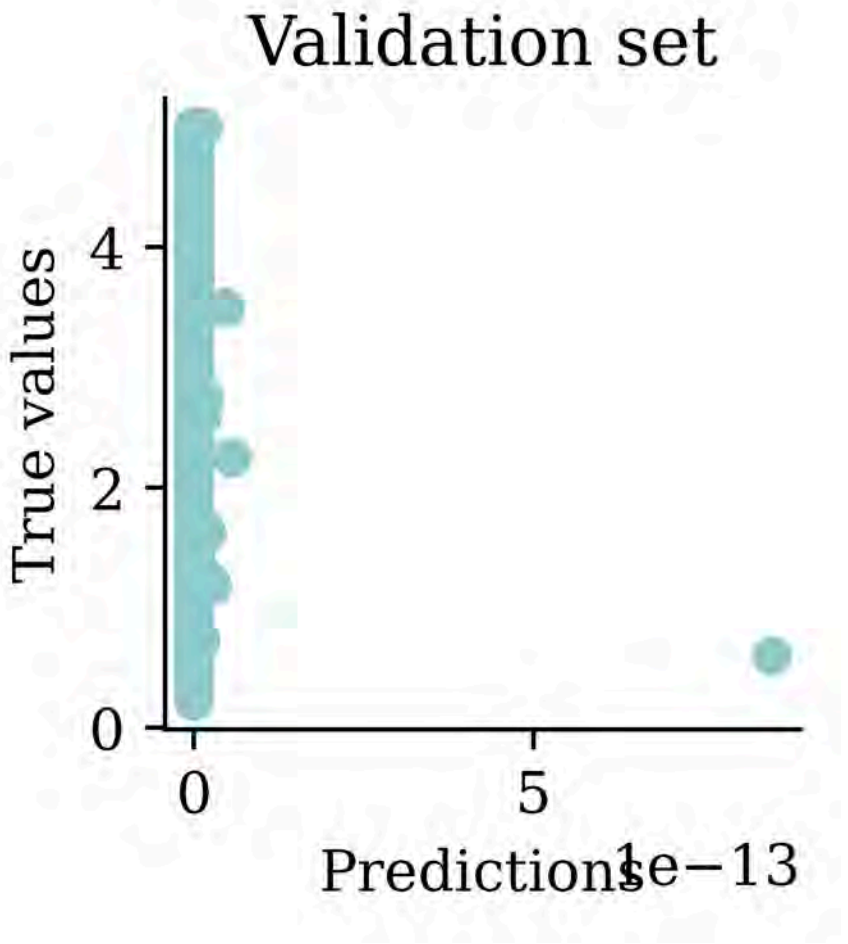
Enforce positive outputs (softplus)

```
random.seed(123)

model = Sequential([
    Dense(30, activation="leaky_relu"),
    Dense(1, activation="softplus")
])

model.compile("adam", "mse")

%time hist = model.fit(X_train, y_train, epochs=50, \
    verbose=False)

losses = np.round(hist.history["loss"], 2)
print(losses[:5], " ... ", losses[-5:])
```

```
CPU times: user 33.8 s, sys: 930 ms, total: 34.7 s
Wall time: 34.1 s
[5.65 5.64 5.64 5.64 5.64] ... [5.64 5.64 5.64 5.64 5.64]
```

Plot the predictions





Enforce positive outputs (e^x)

```
random.seed(123)

model = Sequential([
    Dense(30, activation="leaky_relu"),
    Dense(1, activation="exponential")
])

model.compile("adam", "mse")

%time hist = model.fit(X_train, y_train, epochs=5, verbose=False)

losses = hist.history["loss"]
print(losses)
```

```
CPU times: user 3.43 s, sys: 84.2 ms, total: 3.51 s
Wall time: 3.45 s
[50286.49609375, 6.613603591918945, 6.612048149108887, 6.609488010406494, 6.605171203613281]
```

Same as transforming the target

4.1. Model

We fitted the following model:

$$\begin{aligned}\ln(\text{MEDIAN VALUE}) = {} & \text{INTERCEPT} + \beta_2\,\text{MEDIAN INCOME} + \beta_3\,\text{MEDIAN INCOME}^2 + \beta_4\,\text{MEDIAN INCOME}^3 \\ & + \beta_5 \ln(\text{MEDIAN(AGE)}) + \beta_6 \ln(\text{TOTAL ROOMS/POPULATION}) \\ & + \beta_7 \ln(\text{BEDROOMS/POPULATION}) + \beta_8 \ln(\text{POPULATION/HOUSEHOLDS}) \\ & + \beta_9 \ln(\text{HOUSEHOLDS}) \end{aligned} \tag{8}$$

The polynomial regression used by researchers who first studied this dataset.

> **Note**
>
> Fitting ln(Median Value) is mathematically identical to the `exponential` activation function in the final layer (but metrics are in different units).

Source: Pace and Barry (1997), Sparse Spatial Autoregressions, Statistics & Probability Letters.

Good to know others results

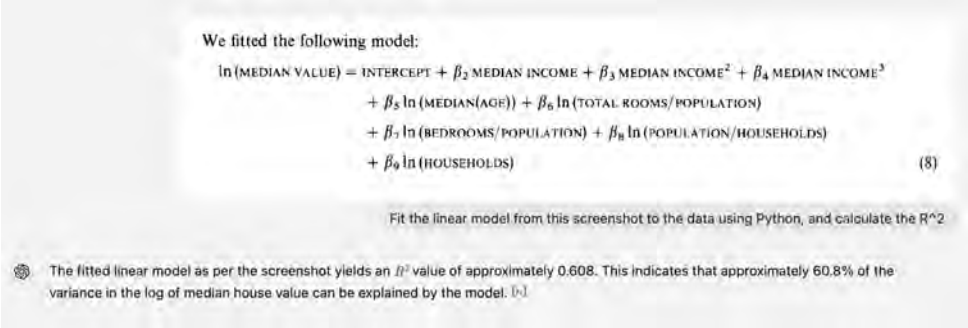
Table 1
OLS and SAR estimates for median housing prices across 20 640 California census block groups

	B_{ols}	t_{ols}	B_{sar}	t_{sar}
INTERCEPT	11.4939	275.7518	11.6637	402.5925
MEDIAN INCOME	0.4790	45.7768	0.0349	4.7104
MEDIAN INCOME^2	−0.0166	−9.4841	0.0100	8.4280
MEDIAN INCOME^3	−0.0002	−1.9157	−0.0007	−12.2444
ln (MEDIAN AGE)	0.1570	33.6123	−0.0421	−11.0942
ln(TOTAL ROOMS/POPULATION)	−0.8582	−56.1280	0.3098	24.5768
ln(BEDROOMS/POPULATION)	0.8043	38.0685	−0.1926	−11.8049
ln (POPULATION/HOUSEHOLDS)	−0.4077	−20.8762	−0.0342	−2.3582
ln (HOUSEHOLDS)	0.0477	13.0792	0.0034	1.5569
α			0.8536	
R^2	0.6078		0.8594	
Median $\|e\|$	0.2101		0.1084	
Execution time			1130 s	
Number of likelihood evaluations			10	

That basic model gets R^2 of 0.61, but their fancy model gets 0.86.

Source: Pace and Barry (1997), Sparse Spatial Autoregressions, Statistics & Probability Letters.

GPT can double-check these results



We fitted the following model:

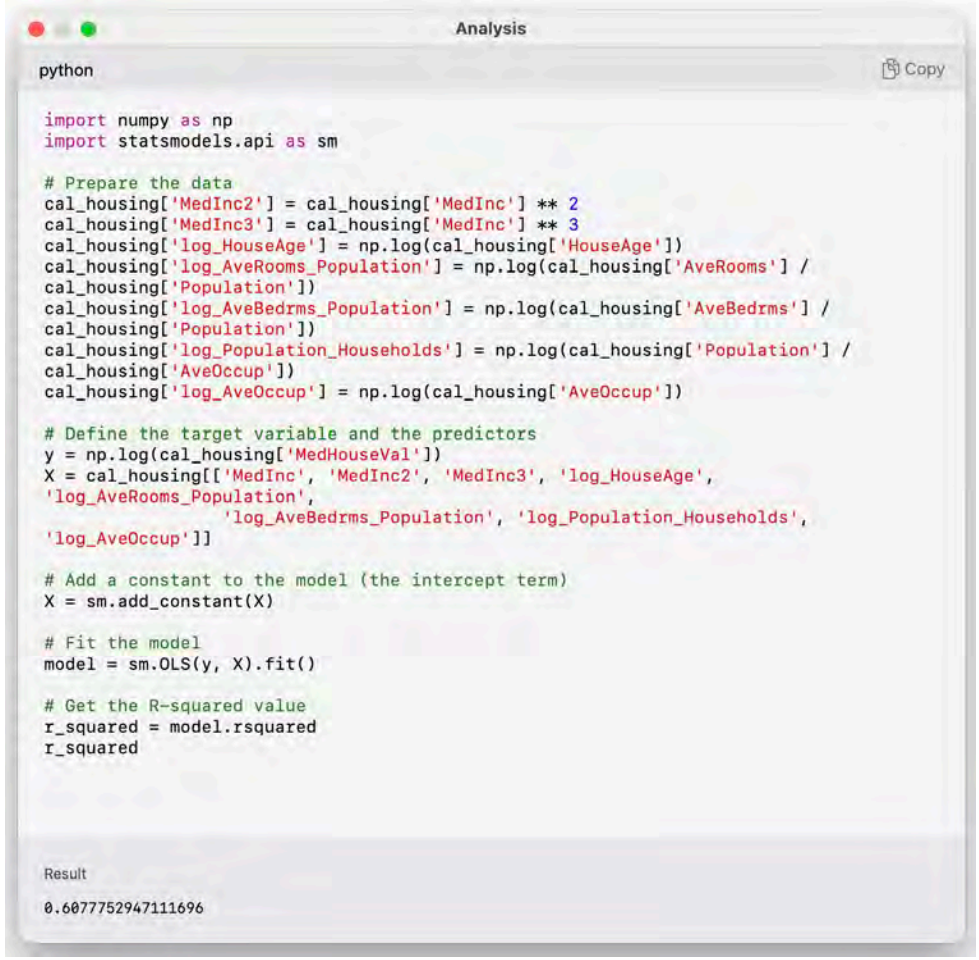
$$\ln(\text{MEDIAN VALUE}) = \text{INTERCEPT} + \beta_2\,\text{MEDIAN INCOME} + \beta_3\,\text{MEDIAN INCOME}^2 + \beta_4\,\text{MEDIAN INCOME}^3 + \beta_5 \ln(\text{MEDIAN(AGE)}) + \beta_6 \ln(\text{TOTAL ROOMS/POPULATION}) + \beta_7 \ln(\text{BEDROOMS/POPULATION}) + \beta_8 \ln(\text{POPULATION/HOUSEHOLDS}) + \beta_9 \ln(\text{HOUSEHOLDS}) \quad (8)$$

Fit the linear model from this screenshot to the data using Python, and calculate the R^2

The fitted linear model as per the screenshot yields an R^2 value of approximately 0.608. This indicates that approximately 60.8% of the variance in the log of median house value can be explained by the model.

Asking GPT to check it.

I'd previously given it the CSV of the data.



Analysis

python

Copy

```
import numpy as np
import statsmodels.api as sm

# Prepare the data
cal_housing['MedInc2'] = cal_housing['MedInc'] ** 2
cal_housing['MedInc3'] = cal_housing['MedInc'] ** 3
cal_housing['log_HouseAge'] = np.log(cal_housing['HouseAge'])
cal_housing['log_AveRooms_Population'] = np.log(cal_housing['AveRooms'] /
cal_housing['Population'])
cal_housing['log_AveBedrms_Population'] = np.log(cal_housing['AveBedrms'] /
cal_housing['Population'])
cal_housing['log_Population_Households'] = np.log(cal_housing['Population'] /
cal_housing['AveOccup'])
cal_housing['log_AveOccup'] = np.log(cal_housing['AveOccup'])

# Define the target variable and the predictors
y = np.log(cal_housing['MedHouseVal'])
X = cal_housing[['MedInc', 'MedInc2', 'MedInc3', 'log_HouseAge',
'log_AveRooms_Population',
                 'log_AveBedrms_Population', 'log_Population_Households',
'log_AveOccup']]

# Add a constant to the model (the intercept term)
X = sm.add_constant(X)

# Fit the model
model = sm.OLS(y, X).fit()

# Get the R-squared value
r_squared = model.rsquared
r_squared
```

Result

```
0.6077752947111696
```

The code it wrote & ran.

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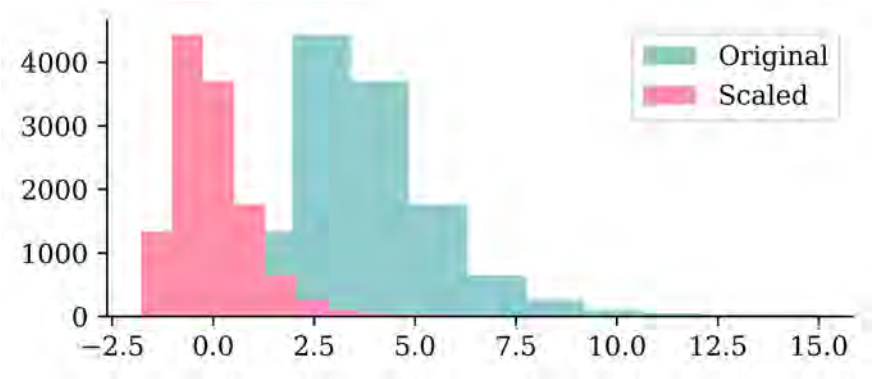
- Early Stopping

Re-scaling the inputs

```
scaler = StandardScaler()
scaler.fit(X_train)

X_train_sc = scaler.transform(X_train)
X_val_sc = scaler.transform(X_val)
X_test_sc = scaler.transform(X_test)
```

```
plt.hist(X_train.iloc[:, 0])
plt.hist(X_train_sc[:, 0])
plt.legend(["Original", "Scaled"]);
```



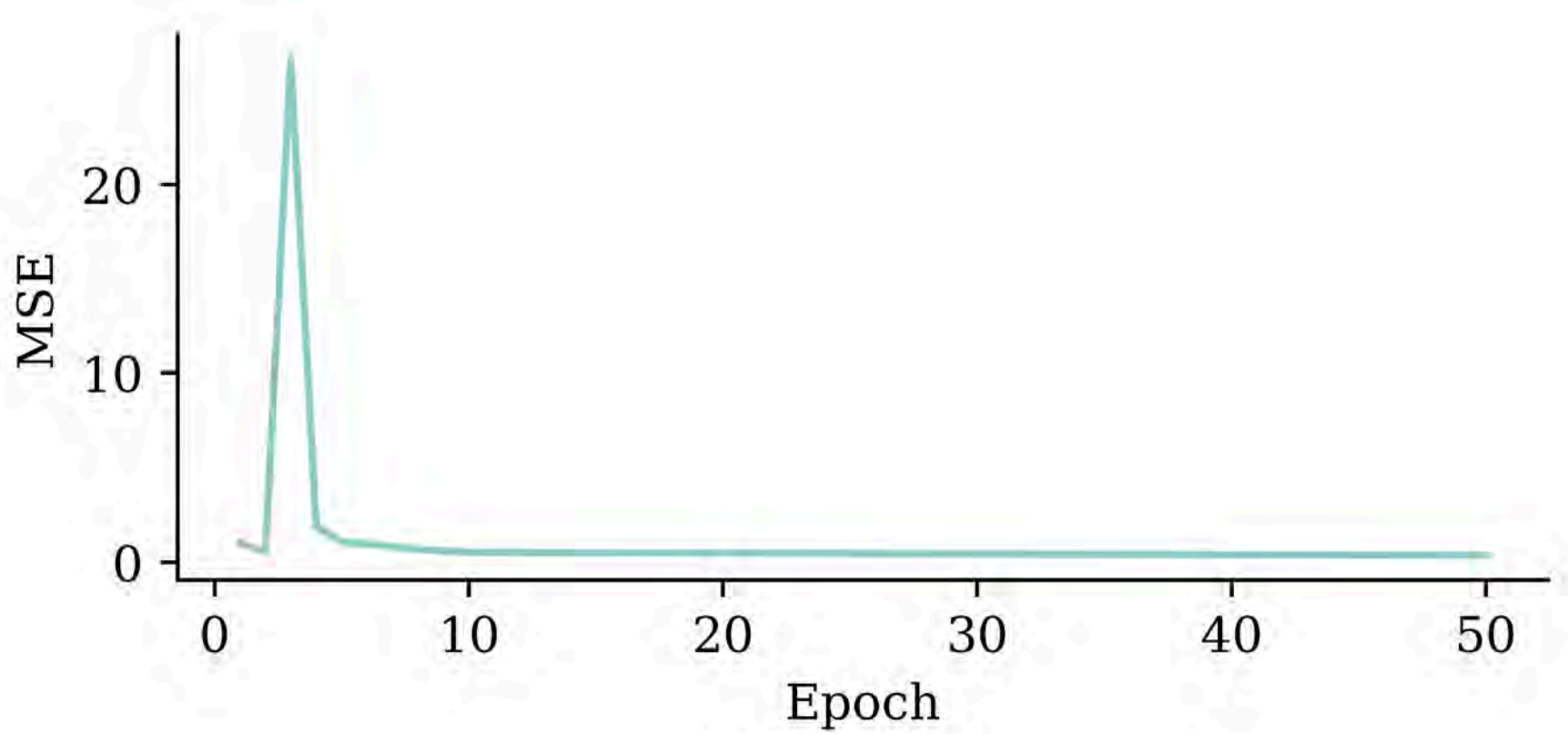
Same model with scaled inputs

```
random.seed(123)

model = Sequential([
    Dense(30, activation="leaky_relu"),
    Dense(1, activation="exponential")
])

model.compile("adam", "mse")

%time hist = model.fit( \
    X_train_sc, \
    y_train, \
    epochs=50, \
    verbose=False)
```

```
CPU times: user 33.1 s, sys: 768 ms, total: 33.8 s
Wall time: 33.3 s
```

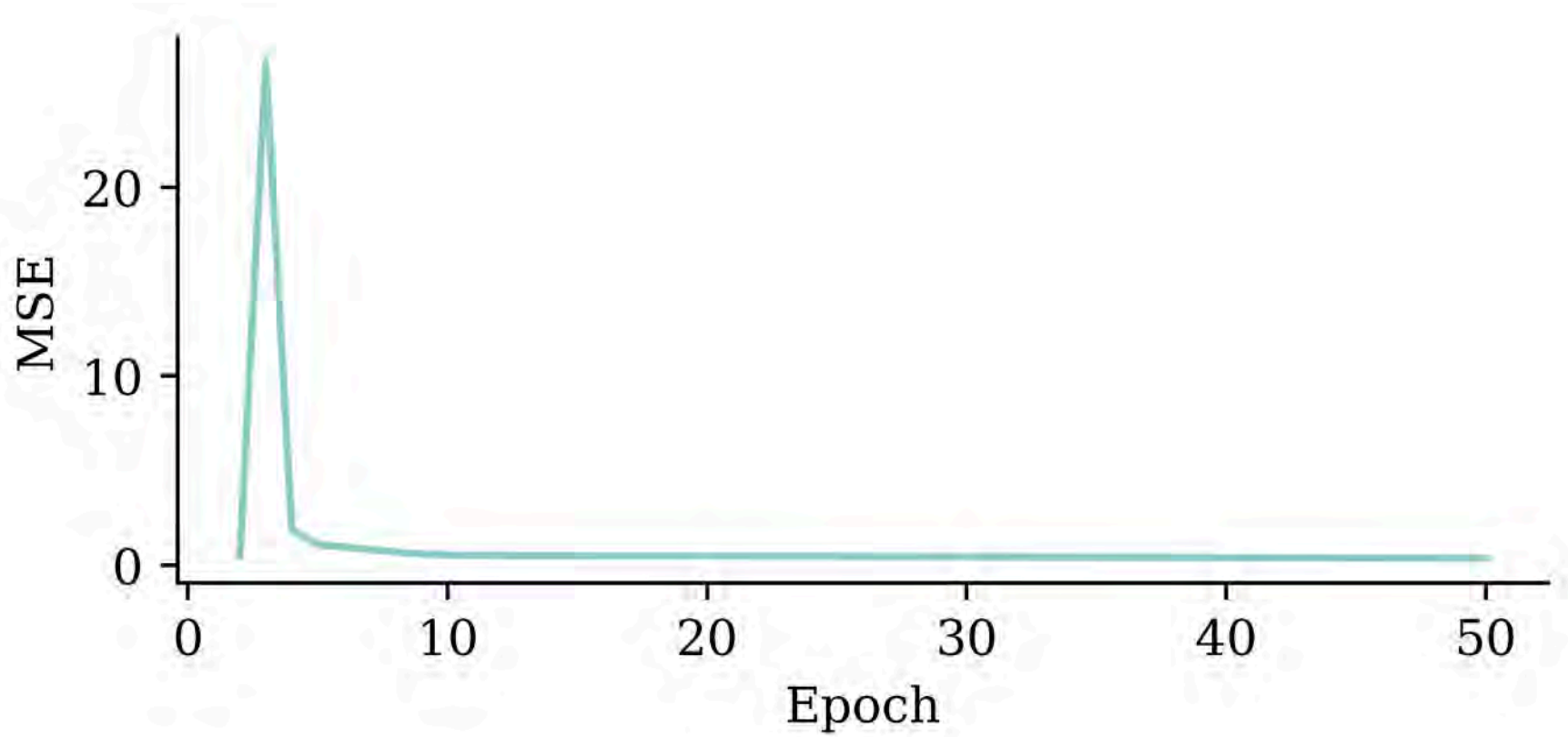
Loss curve

```
1 plt.plot(range(1, 51), hist.history["loss"])
2 plt.xlabel("Epoch")
3 plt.ylabel("MSE");
```



Loss curve

```
1 plt.plot(range(2, 51), hist.history["loss"][1:])
2 plt.xlabel("Epoch")
3 plt.ylabel("MSE");
```



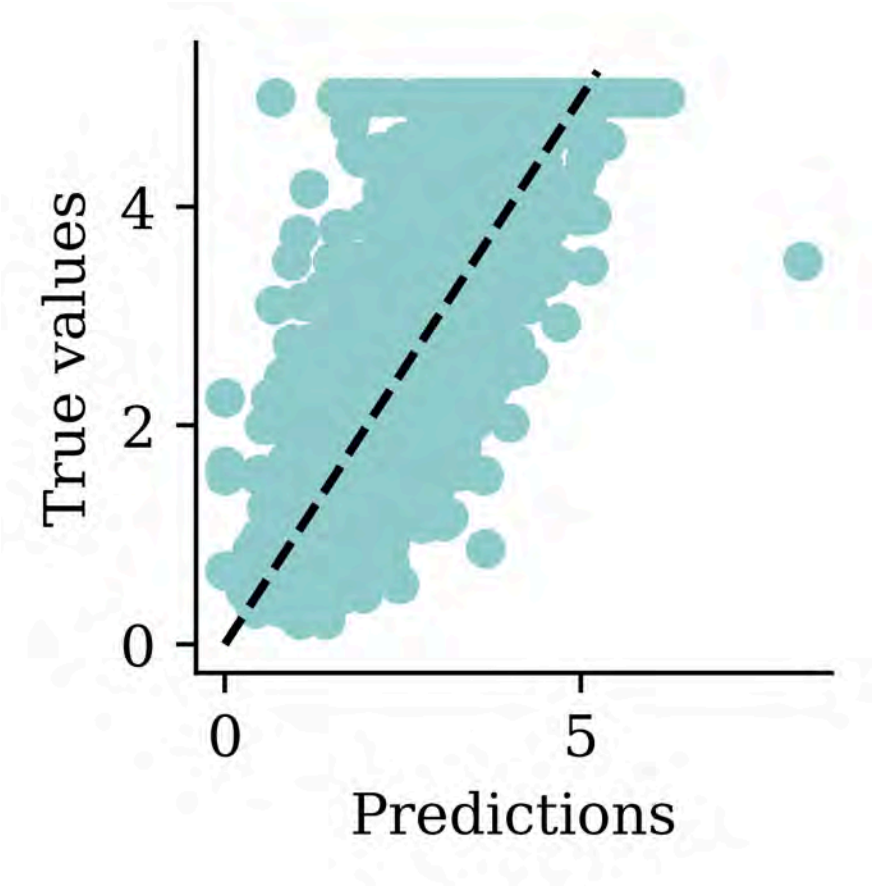
Predictions

```
y_pred = model.predict(X_val_sc, verbose=0)
print(f"Min prediction: {y_pred.min():.2f}")
print(f"Max prediction: {y_pred.max():.2f}")
```

```
Min prediction: 0.00
Max prediction: 8.11
```

```
plt.scatter(y_pred, y_val)
plt.xlabel("Predictions")
plt.ylabel("True values")
add_diagonal_line()
```

```
mse_train["Exp ANN"] = mean_squared_error
    y_train, model.predict(X_train_sc, ve
)
mse_val["Exp ANN"] = mean_squared_error(y
```



UNSW SYDNEY

Comparing MSE (smaller is better)

On training data:

```
1 mse_train
```

```
{'Linear Regression': 0.5291948207479792,
 'Basic ANN': 2.8278137790106026,
 'Long run ANN': 0.5999134938371403,
 'Exp ANN': 0.35574261079097375}
```

On validation data (expect *worse*, i.e. bigger):

```
1 mse_val
```

```
{'Linear Regression': 0.5059420205381369,
 'Basic ANN': 2.845539574957286,
 'Long run ANN': 0.6106608478598903,
 'Exp ANN': 0.347549802095409}
```

Comparing models (train)

```
train_results = pd.DataFrame(
    {"Model": mse_train.keys(), "MSE": mse_train.values()}
)
train_results.sort_values("MSE", ascending=False)
```

	Model	MSE
1	Basic ANN	2.827814
2	Long run ANN	0.599913
0	Linear Regression	0.529195
3	Exp ANN	0.355743

Comparing models (validation)

```
val_results = pd.DataFrame(
    {"Model": mse_val.keys(), "MSE": mse_val.values()}
)
val_results.sort_values("MSE", ascending=False)
```

	Model	MSE
1	Basic ANN	2.845540
2	Long run ANN	0.610661
0	Linear Regression	0.505942
3	Exp ANN	0.347550

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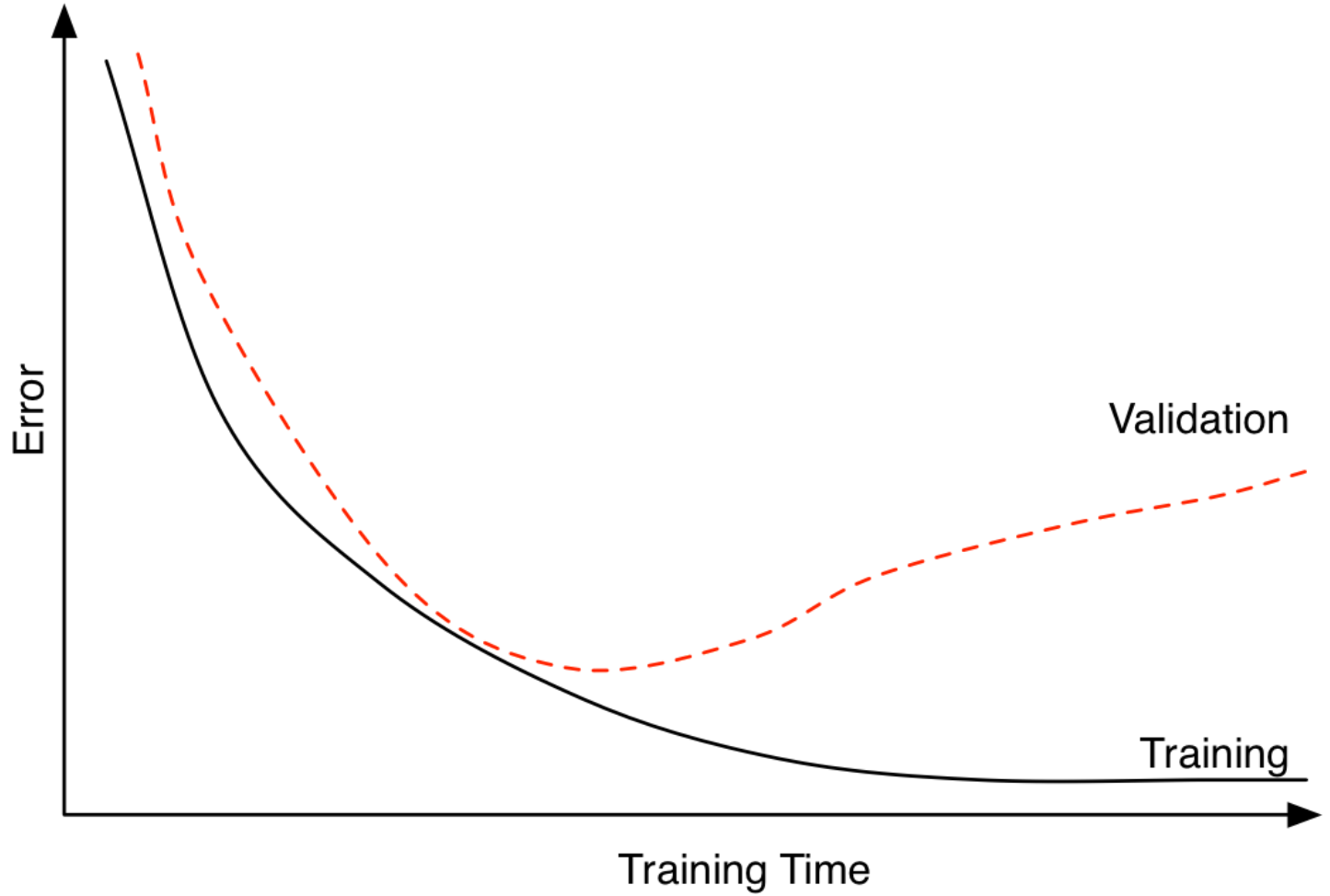
Choosing when to stop training



Illustrative loss curves over time.

Source: Heaton (2022), Applications of Deep Learning, Part 3.4: Early Stopping.

Try early stopping

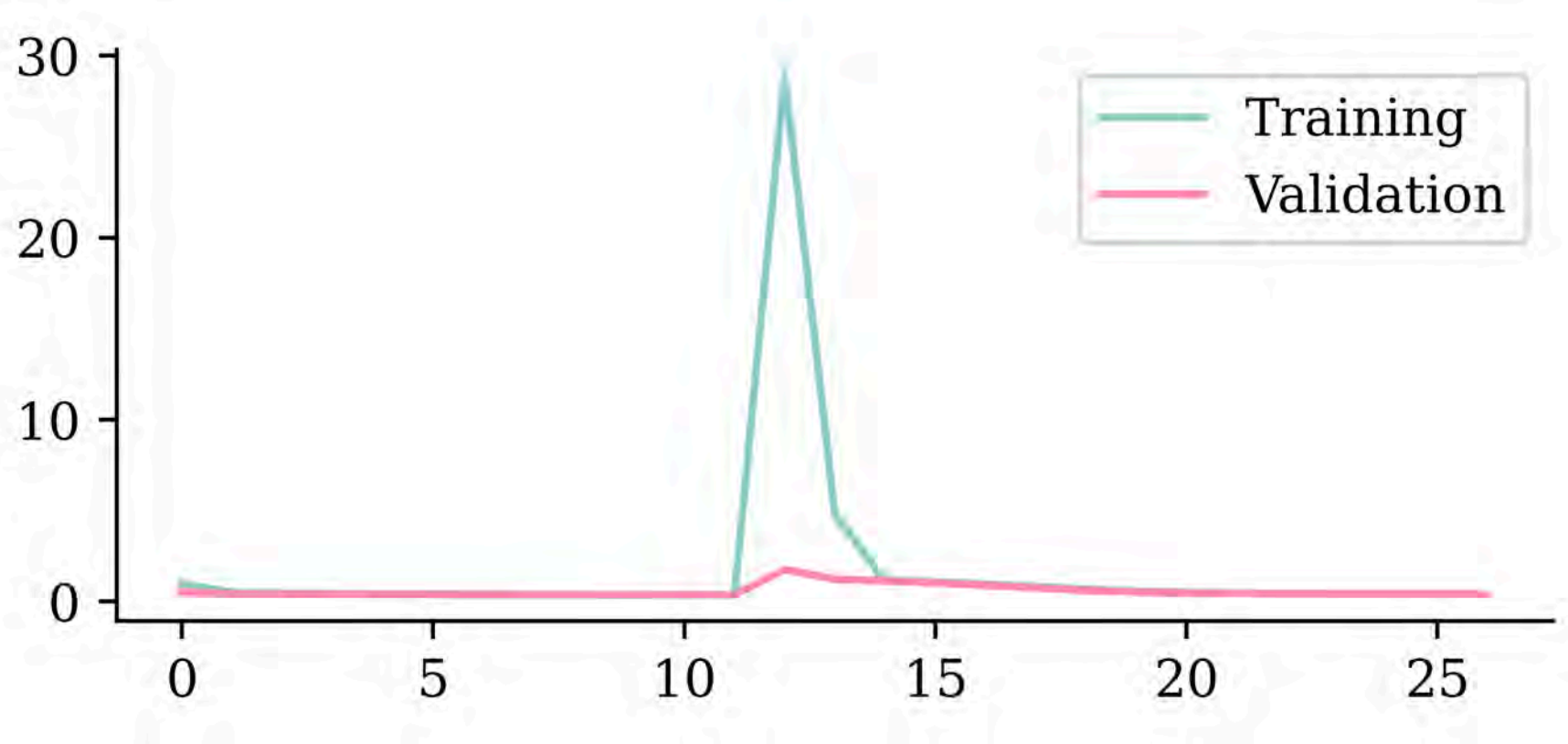
Hinton calls it a “beautiful free lunch”

```
random.seed(123)
model = Sequential([
    Dense(30, activation="leaky_relu"),
    Dense(1, activation="exponential")
])
model.compile("adam", "mse")

es = EarlyStopping(restore_best_weights=True, patience=15)

%time hist = model.fit(X_train_sc, y_train, epochs=1_000, \
    callbacks=[es], validation_data=(X_val_sc, y_val), verbose=False)
print(f"Keeping model at epoch #{len(hist.history['loss'])-15}.")
```

```
CPU times: user 22.7 s, sys: 631 ms, total: 23.4 s
Wall time: 22.9 s
Keeping model at epoch #12.
```

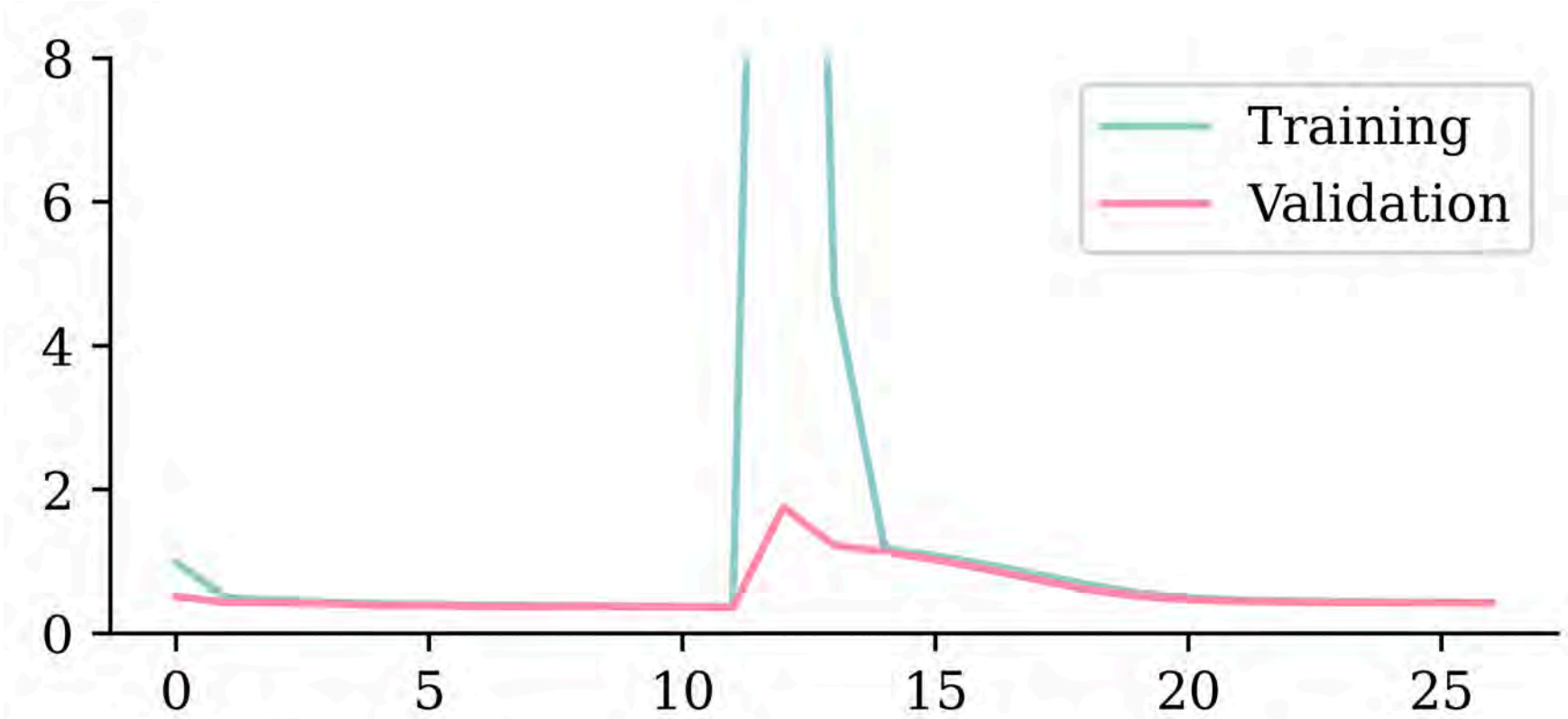
Loss curve

```
1 plt.plot(hist.history["loss"])
2 plt.plot(hist.history["val_loss"])
3 plt.legend(["Training", "Validation"]);
```

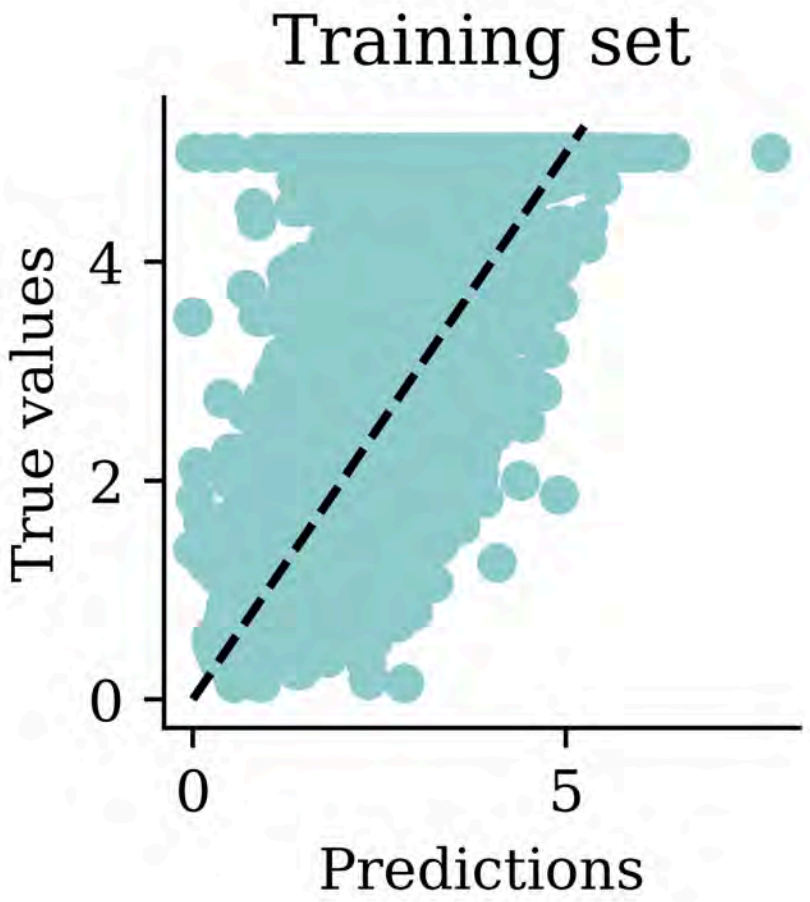


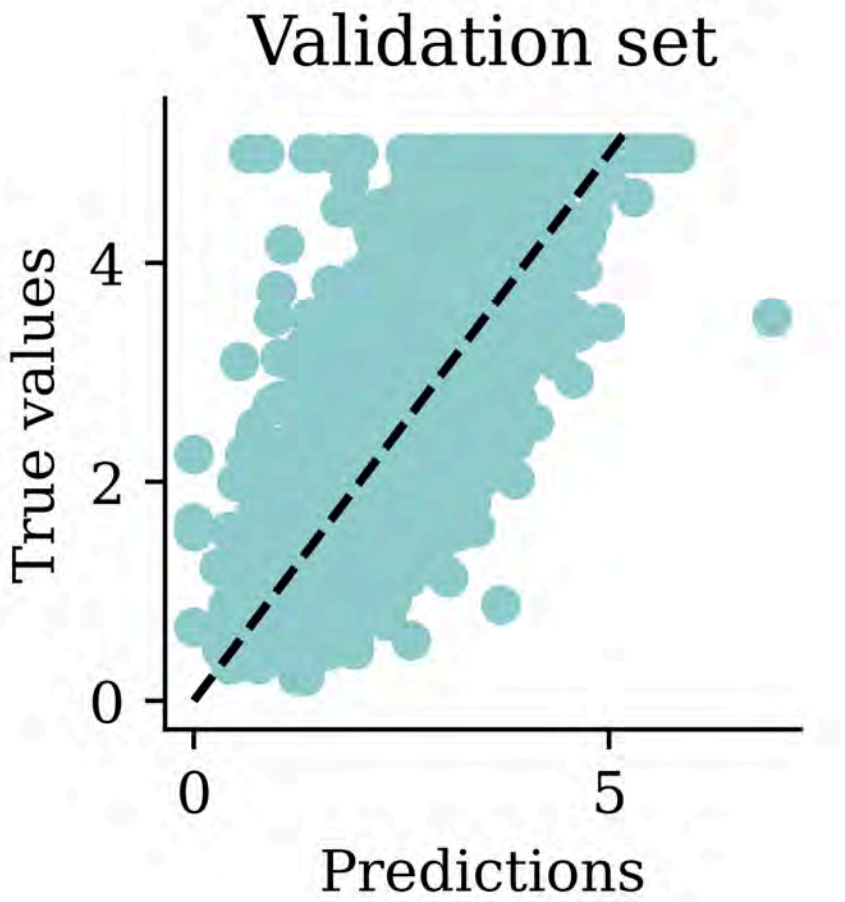
Loss curve II

```
1 plt.plot(hist.history["loss"])
2 plt.plot(hist.history["val_loss"])
3 plt.ylim([0, 8])
4 plt.legend(["Training", "Validation"]);
```



Predictions





Comparing models (validation)

	Model	MSE
1	Basic ANN	2.845540
2	Long run ANN	0.610661
0	Linear Regression	0.505942
4	Early stop ANN	0.359737
3	Exp ANN	0.347550

The test set

Evaluate *only the final/selected model* on the test set.

```
1 mean_squared_error(y_test, model.predict(X_test_sc, verbose=0))
```

```
0.36174060505869826
```

```
1 model.evaluate(X_test_sc, y_test, verbose=False)
```

```
0.3617406189441681
```

Another useful callback

```
random.seed(123)
model = Sequential(
    [Dense(30, activation="leaky_relu"), Dense(1, activation="exponential")]
)
model.compile("adam", "mse")
mc = ModelCheckpoint(
    "best-model.keras", monitor="val_loss", save_best_only=True
)
es = EarlyStopping(restore_best_weights=True, patience=5)
hist = model.fit(
    X_train_sc,
    y_train,
    epochs=100,
    validation_split=0.1,
    callbacks=[mc, es],
    verbose=False,
)
Path("best-model.keras").stat().st_size
```

```
24584
```

Keras model methods

- `compile`: specify the loss function and optimiser
- `fit`: learn the parameters of the model
- `predict`: apply the model
- `evaluate`: apply the model and calculate a metric

```
random.seed(12)
model = Sequential()
model.add(Dense(1, activation="relu"))
model.compile("adam", "poisson")
model.fit(X_train, y_train, verbose=0)
y_pred = model.predict(X_val, verbose=0)
print(model.evaluate(X_val, y_val, verbose=0))
```

```
4.442193984985352
```

Package Versions

```
1 from watermark import watermark
2 print(watermark(python=True, packages="keras,matplotlib,numpy,pandas,seaborn,scipy,torch"
```

```
Python implementation: CPython
Python version       : 3.14.3
IPython version      : 9.13.0

keras     : 3.14.1
matplotlib: 3.10.9
numpy     : 2.4.4
pandas    : 3.0.2
seaborn   : 0.13.2
scipy     : 1.17.1
torch     : 2.11.0
```

Glossary

- activations, activation function
- artificial neural network
- biases (in neurons)
- callbacks
- classification problem
- cost/loss function
- deep network, network depth
- dense or fully-connected layer
- early stopping
- epoch
- feed-forward neural network
- Keras, TensorFlow, PyTorch
- labelled/unlabelled data
- machine learning
- matplotlib
- minimax algorithm
- neural network architecture
- perceptron
- ReLU
- representation learning
- sigmoid activation function
- targets
- training/validation/test split
- weights (in a neuron)

References

Shang, Z., Chauhan, V., Devi, K., & Patil, S. (2025). Artificial intelligence, the digital surgeon: Unravelling its emerging footprint in healthcare – the narrative review. *Journal of Multidisciplinary Healthcare*, *17*, 4011–4022.