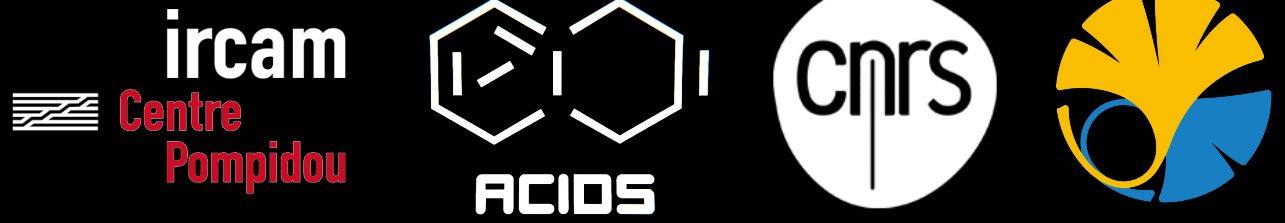

Machine Learning

Creative Machine Learning - Course 01

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Machine learning

Problem statement

We witness a phenomenon
Through a set of observations

$$(x_1, y_1)\ (x_2, y_2)\ \cdots\ (x_n, y_n)$$

We know there exists a relation between $\mathcal{X}$ and $\mathcal{Y}$

But we do not know its nature

$$f : \mathcal{X} \to \mathcal{Y}$$

Machine learning constructs approximations

$$f_\theta : \mathcal{X} \to \mathcal{Y}$$

such that

$$y_i \approx \bar{y}_i = f_\theta(x_i)$$

Regression and classification

The two most classical machine learning problems

Machine learning

Formal problem statement

We aim to model the relationship between $\mathcal{X}$ and $\mathcal{Y}$

$$f : \mathcal{X} \to \mathcal{Y}$$

We collect a **dataset** that is representative of that relation

$$\mathcal{D} = \{(\mathbf{x}_1, \mathbf{y}_1) \cdots (\mathbf{x}_n, \mathbf{y}_n)\}$$

We will construct a **parametric approximation** $f_\theta \in \mathcal{F}_\Theta$

$$f_\theta : \mathcal{X} \to \mathcal{Y} \quad \bar{\mathbf{y}} = f_\theta(\mathbf{x})$$

We want to find the best f_θ^* so that $\bar{\mathbf{y}} \approx \mathbf{y}$

So we need to find the best parameters $\theta^* \in \Theta$

Need to compute the errors (**loss**) of our model

$$\mathcal{L}(\bar{\mathbf{y}}, \mathbf{y} \mid f_\theta, \theta)$$

And minimize (**optimize**) this amount of errors

$$\theta^* = \underset{\theta}{\operatorname{argmin}}\ \mathcal{L}(\bar{\mathbf{y}}, \mathbf{y} \mid f_\theta, \theta)$$

Key elements of our problem definition

Dataset

$$\mathcal{D} = \{(\mathbf{x}_1, \mathbf{y}_1) \cdots (\mathbf{x}_n, \mathbf{y}_n)\}$$

The **dataset** has to be **representative** of the relation $f : \mathcal{X} \to \mathcal{Y}$

Model

$$f_\theta : \mathcal{X} \to \mathcal{Y} \qquad \bar{\mathbf{y}} = f_\theta(\mathbf{x})$$

The choice of **parametric family** $f_\theta \in \mathcal{F}_\Theta$ is critical

Loss

$$\mathcal{L}(\bar{\mathbf{y}}, \mathbf{y} \mid f_\theta, \theta)$$

How do we measure the errors (**loss**) of our model

Optimization

Search for best $\theta^* \in \Theta$ so f_{θ^*} minimizes the loss ($\bar{\mathbf{y}} \approx \mathbf{y}$)

$$\theta^* = \underset{\theta}{\operatorname{argmin}}\ \mathcal{L}(\bar{\mathbf{y}}, \mathbf{y} \mid f_\theta, \theta)$$

How to choose the parametric family ?

Choice of approximation family (model)

Quality depends heavily on family $\mathcal{F}_\theta$

Notion of *model capacity*

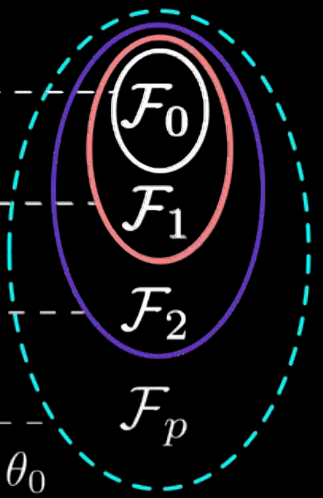
Approximation families

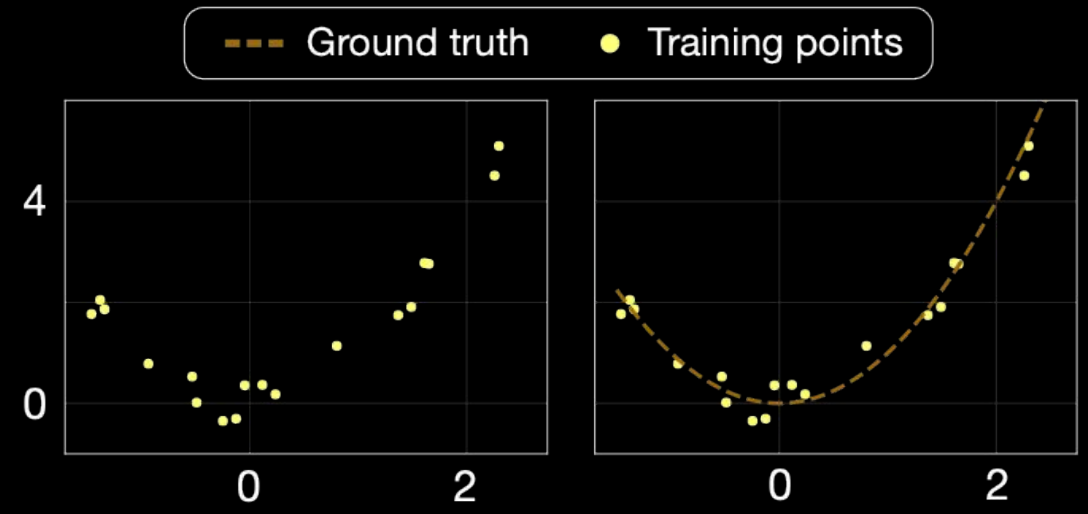
Constant
$\mathcal{F}_0(x) = \theta_0$

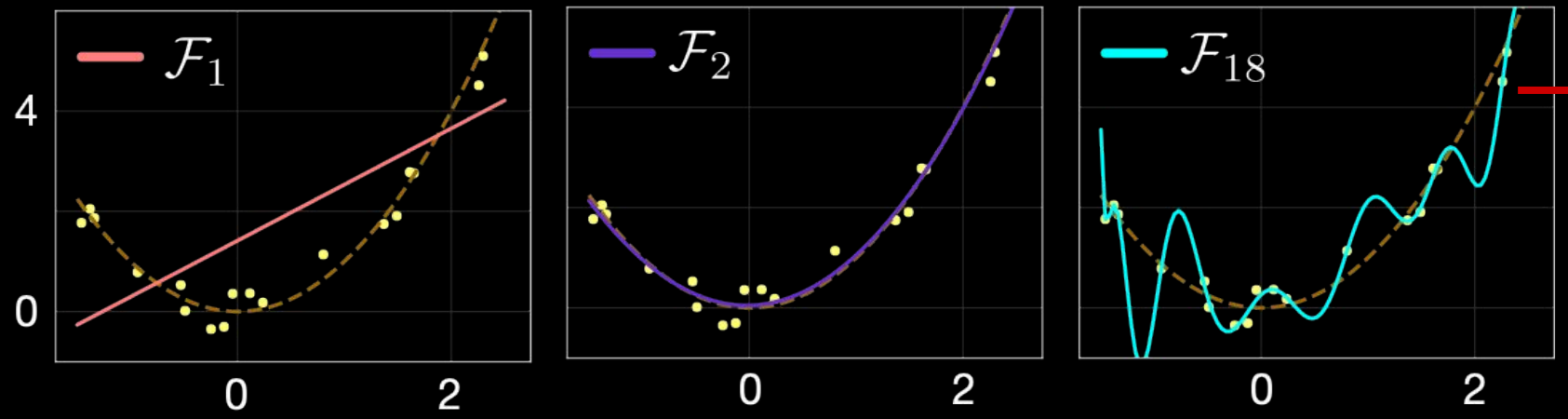
Linear
$\mathcal{F}_1(x) = \theta_1 x + \theta_0$

Square
$\mathcal{F}_2(x) = \theta_2 x^2 + \theta_1 x + \theta_0$

Polynomial
$\mathcal{F}_p(x) = \theta_p x^p + \cdots + \theta_1 x + \theta_0$







Overfitting

("Because it can")

We will see how we can solve this through **regularization**

Linear regression

Supervised learning algorithm

Model the relationship between **one** output (target) and one or more inputs (features).

$$\mathbf{x} \in \mathbb{R}^n \quad \mathcal{X} \xrightarrow{f_\theta} \mathcal{Y} \quad y \in \mathbb{R}$$

Input (feature) *Output (target)*

Regression

Linear regression

Supervised learning algorithm

Model the relationship between **one** output (target) and one or more inputs (features).

$$\underset{\text{Input (feature)}}{\mathbf{x} \in \mathbb{R}^n} \quad \mathcal{X} \xrightarrow{f_\theta} \mathcal{Y} \quad \underset{\text{Output (target)}}{y \in \mathbb{R}}$$

Goal Find best-fitting *hyperplane* (*line*) to predict output.

Equation $y = w_0 + w_1 x_1 + w_2 x_2 + \ldots + w_n x_n + \epsilon$

- y : Output (*target*)
- x_i : Input (*feature*)
- w_i : Coefficients (*weights*)
- w_0 : Intercept (*bias* term)
- ϵ : Residual error

A note on the residual error ϵ Modeling the observation noise always present

Model $f_\theta(x) = \bar{y} = w_0 + w_1 x_1 + \cdots + w_n x_n$

Modify parameters $\theta = \{w_0, \cdots, w_n\}$ so that $y \approx \bar{y}$

Best-fitting line ? *Minimize differences between real and predicted output*

Various application in inference and forecasting.

Simple linear regression

Principle

Linear regression with a **single input** variable.
Model relationship of *single* input and output (*target*).

$$x \in \mathbb{R} \longrightarrow y \in \mathbb{R}$$

Examples: *Predicting house prices based on sizes, predicting temperature based on year*

Model $\bar{y} = w_0 + w_1 x \quad \theta = \{w_0, w_1\}$

Based on our collected dataset of examples $\mathcal{D} = \{(x_1, y_1), \cdots, (x_n, y_n)\}$

We can compute the errors made by our model **on each example**

$$\epsilon_i = |y_i - \bar{y}_i| = |y_i - (w_0 + w_1 x_i)| \quad \text{—— } L_1 \text{ loss}$$

L_2 loss function
Mean-Squared Error (MSE)

$$\mathcal{L}_{MSE}(\bar{\mathbf{y}}, \theta) = \sum_{i=1}^{n} |y_i - \bar{y}_i|^2 = \sum_{i=1}^{n} |y_i - (w_0 + w_1 x_i)|^2$$

whole dataset

—— **More sensitive to outliers (square)**

Goal $\underset{\theta}{\operatorname{argmin}}\ \mathcal{L}(\bar{\mathbf{y}}, \theta)$ Minimize the MSE based on parameters $\theta = \{w_0, w_1\}$

Gradient descent

Intuition How to find the parameters that minimize our loss function ?

$$\min_{\theta} \mathcal{L}(\bar{\mathbf{y}}, \theta) \longrightarrow \frac{\partial \mathcal{L}}{\partial \theta} = 0$$

A minimum exists where the gradient of our function is null

Problems

1. Explicit solution ? Might **require prohibitive computation**
2. Finding minima ? There might be **multiple local minima**
3. **Gradient can change** widely depending on the examples

Gradient descent Optimization algorithm to minimize the loss iteratively.

Compute partial derivatives of the loss w.r.t each parameter.

$$\nabla \mathcal{L}(\mathbf{w}) = \left[\frac{\partial \mathcal{L}}{\partial w_1}, \frac{\partial \mathcal{L}}{\partial w_2}, \dots, \frac{\partial \mathcal{L}}{\partial w_n} \right]$$

Represents the **direction of the steepest increase** of the loss function.

Adjusting parameters in that direction is the steepest decrease of the loss

Gradient descent

Algorithm

1 - Initialize parameters

Start from random point $\mathbf{w} \sim \mathcal{N}(\mu_0, .01)$

2 - Compute partial derivatives

Derive the loss based on all parameters

$$\nabla \mathcal{L}(\mathbf{w}) = \left[\frac{\partial \mathcal{L}}{\partial w_1}, \frac{\partial \mathcal{L}}{\partial w_2}, ..., \frac{\partial \mathcal{L}}{\partial w_n} \right]$$

3 - Iterative updates

In each iteration update the weights

$$\mathbf{w}^{t+1} = \mathbf{w}^t - \eta \nabla \mathcal{L}(\mathbf{w}^t)$$

Move in the opposite direction of the gradient

Learning rate η controls the step size of the updates.

4 - Convergence

Stopping criteria

- $\mathcal{L}(\mathbf{w}) \to 0$
- $\nabla \mathcal{L}(\mathbf{w}) \to 0$
- $t > n_{epochs}$

Understanding the learning rate

Gradient descent optimization

$$\nabla \mathcal{L}(\mathbf{w}) = \left[\frac{\partial \mathcal{L}}{\partial w_1}, \frac{\partial \mathcal{L}}{\partial w_2}, ..., \frac{\partial \mathcal{L}}{\partial w_n}\right]$$

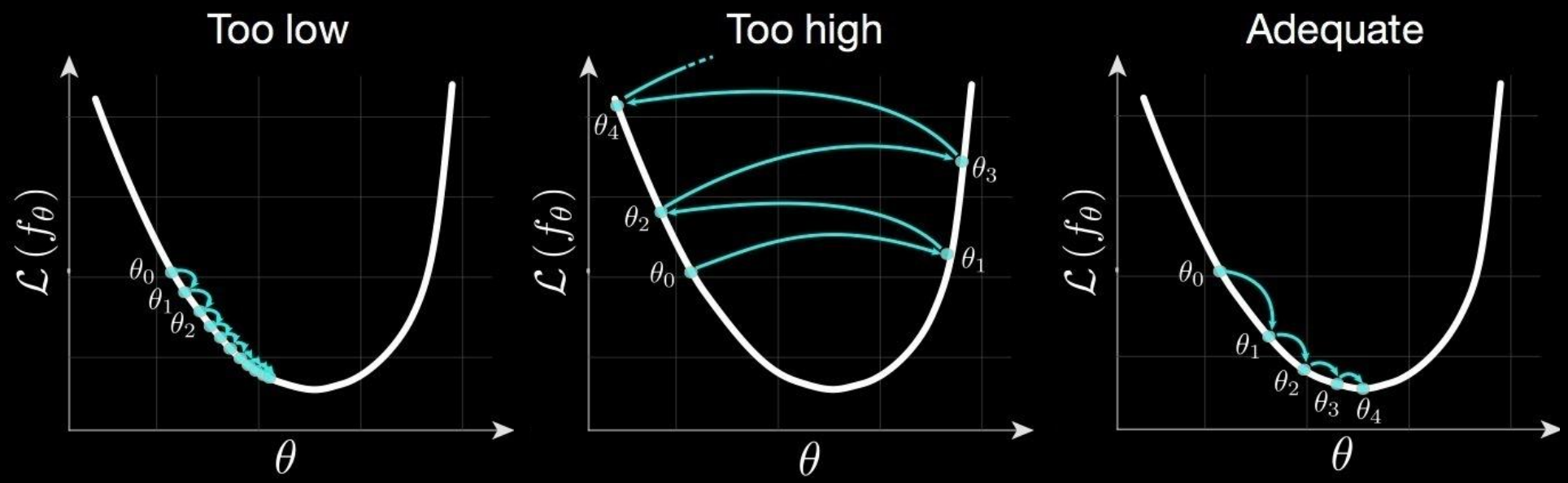
In our previous update equation

$$\mathbf{w}^{t+1} = \mathbf{w}^t - \eta \nabla \mathcal{L}(\mathbf{w}^t)$$

Learning rate η

Impact of the learning rate

Problem is that we do not know the **magnitude** of the gradient



Slow convergence *Divergence*

Applying gradient descent for regression

Goal We want to minimize our loss $\mathcal{L}_{MSE}(\bar{\mathbf{y}}, \theta) = \sum_{i=1}^{n}(y_i - \bar{y}_i)^2 = \sum_{i=1}^{n}(y_i - (w_1 x_i + w_0))^2$

Compute $\nabla\mathcal{L}(\mathbf{w}) = \left[\frac{\partial\mathcal{L}}{\partial w_0}, \frac{\partial\mathcal{L}}{\partial w_1}\right]$

$$\frac{\partial\mathcal{L}}{\partial w_0} = \frac{\partial}{\partial w_0}\left(\sum_{i=1}^{N}(y_i - (w_1 x_i + w_0))^2\right) \quad \frac{\partial\mathcal{L}}{\partial w_1} = \frac{\partial}{\partial w_1}\left(\sum_{i=1}^{N}(y_i - (w_1 x_i + w_0))^2\right)$$

$$\frac{\partial\mathcal{L}}{\partial w_0} = -2\sum_{i=1}^{N}(y_i - (w_1 x_i + w_0))$$

$$\frac{\partial\mathcal{L}}{\partial w_1} = -2\sum_{i=1}^{N} x_i(y_i - (w_1 x_i + w_0))$$

Complete algorithm **Initialize parameters** $w_1^0, w_0^0 \sim \mathcal{N}(0, 1)$

Loop

1. Compute our current **approximation** $\bar{y} = w_1^t x + w_0^t$
2. Compute the current value of the **loss function** $\mathcal{L}_{MSE}(\bar{\mathbf{y}}, \theta) = \sum_{i=1}^{n}\left(y_i - (w_1^t x_i + w_0^t)\right)^2$
3. Compute **gradients** of the loss function

$$\nabla\mathcal{L}(\mathbf{w}) = \left[\frac{\partial\mathcal{L}}{\partial w_0^t}, \frac{\partial\mathcal{L}}{\partial w_1^t}\right] = \left[-2\sum_{i=1}^{N}(y_i - (w_1^t x_i + w_0^t)), -2\sum_{i=1}^{N} x_i(y_i - (w_1^t x_i + w_0^t))\right]$$

4. **Update our parameters** based on the gradients

$$\mathbf{w}^{t+1} = \mathbf{w}^t - \eta\nabla\mathcal{L}(\mathbf{w}^t)$$

Gradient descent variants

So far discussed **batch gradient descent** - compute gradient for the entire dataset

$$\mathbf{w}_{t+1} = \mathbf{w}_t - \eta \frac{1}{N} \sum_i \nabla \mathcal{L}_i(\mathbf{w}_t)$$

Can be slow (or even impossible) for large datasets.

Variants can improve computational efficiency and even convergence properties.

Stochastic GD

Computes gradient with **single data point** each time
Faster than batch-GD, but high variance in updates

$$\mathbf{w}_{t+1} = \mathbf{w}_t - \eta \nabla \mathcal{L}_i(\mathbf{w}_t)$$

Mini-batch GD

$$\mathbf{w}_{t+1} = \mathbf{w}_t - \eta \frac{1}{b} \sum_{i=1}^{b} \nabla \mathcal{L}_i(\mathbf{w}_t)$$

Use a **random subset (mini-batch)** of the dataset.
Trade-off for balancing speed and variance

Adaptive Moment Estimation (ADAM)

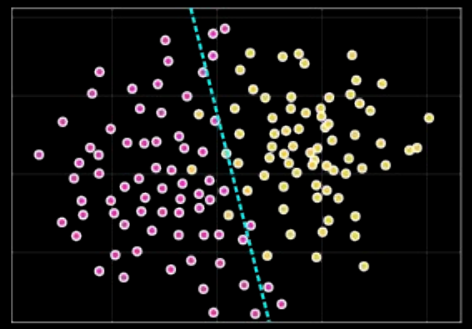
(cf. deep learning)

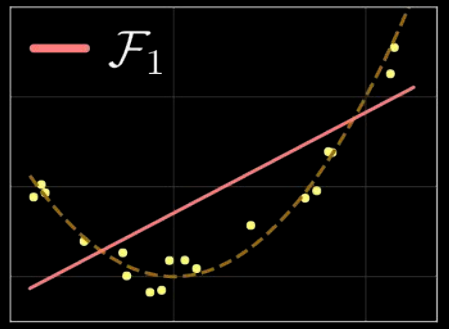
ADAM adapts the learning rate for each parameter
Maintains decaying average of past and squared gradients.
More robust and efficient than standard Gradient Descent.

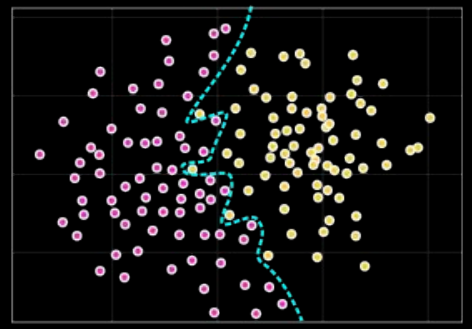
Understanding capacity

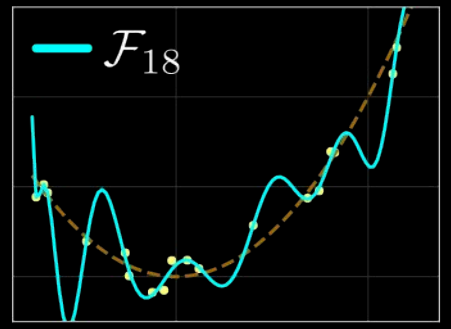
Classification

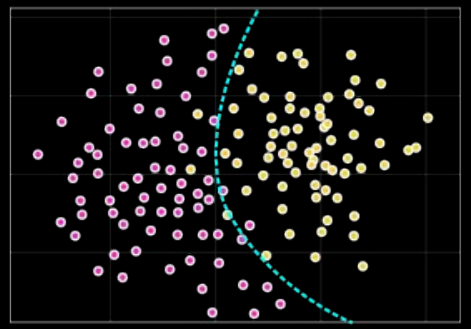
Regression

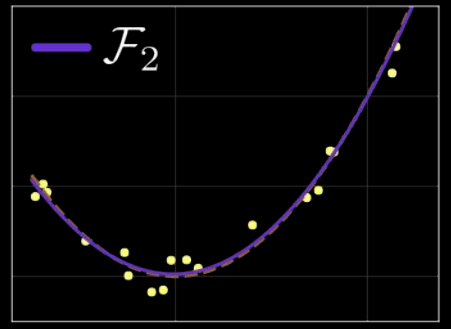












Underfitting

- Function family is **too poor**
- Capacity is **too low** for this problem

Overfitting

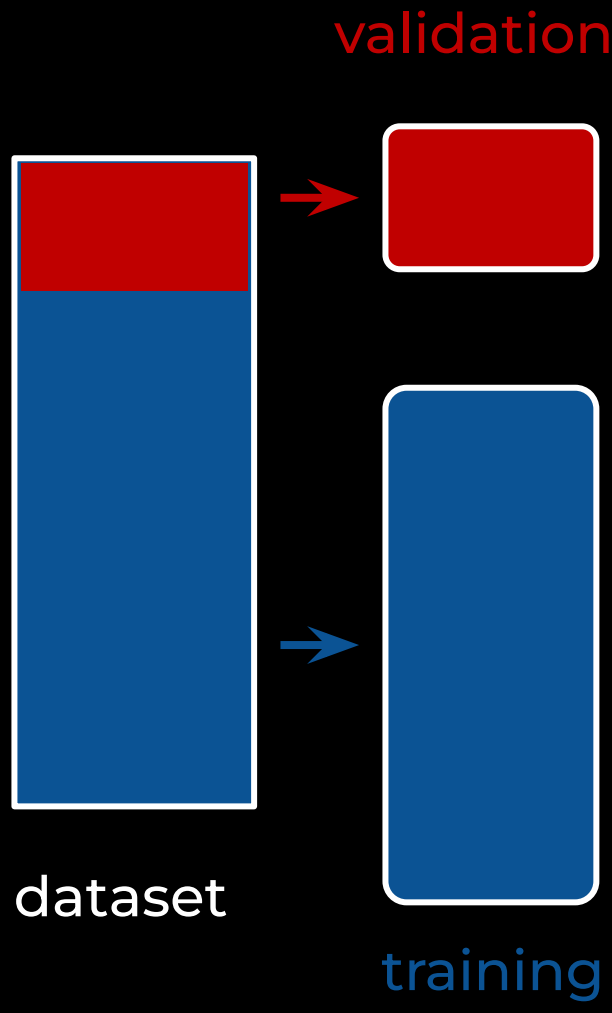
- Function family is **too rich**
- Capacity is **too high** for this problem

Optimal capacity

- Function family is **adequate**
- **Optimal capacity** for this problem

Cross-validation for overfitting

How do we aim to avoid overfitting ?



Split your complete dataset into two distinct set

- **Training** set (~80%) for learning your model
- **Validation** set (~20%) for evaluating overfitting

The validation set emulates an unknown dataset

Allows to evaluate the quality on unseen data

Final performance evaluation

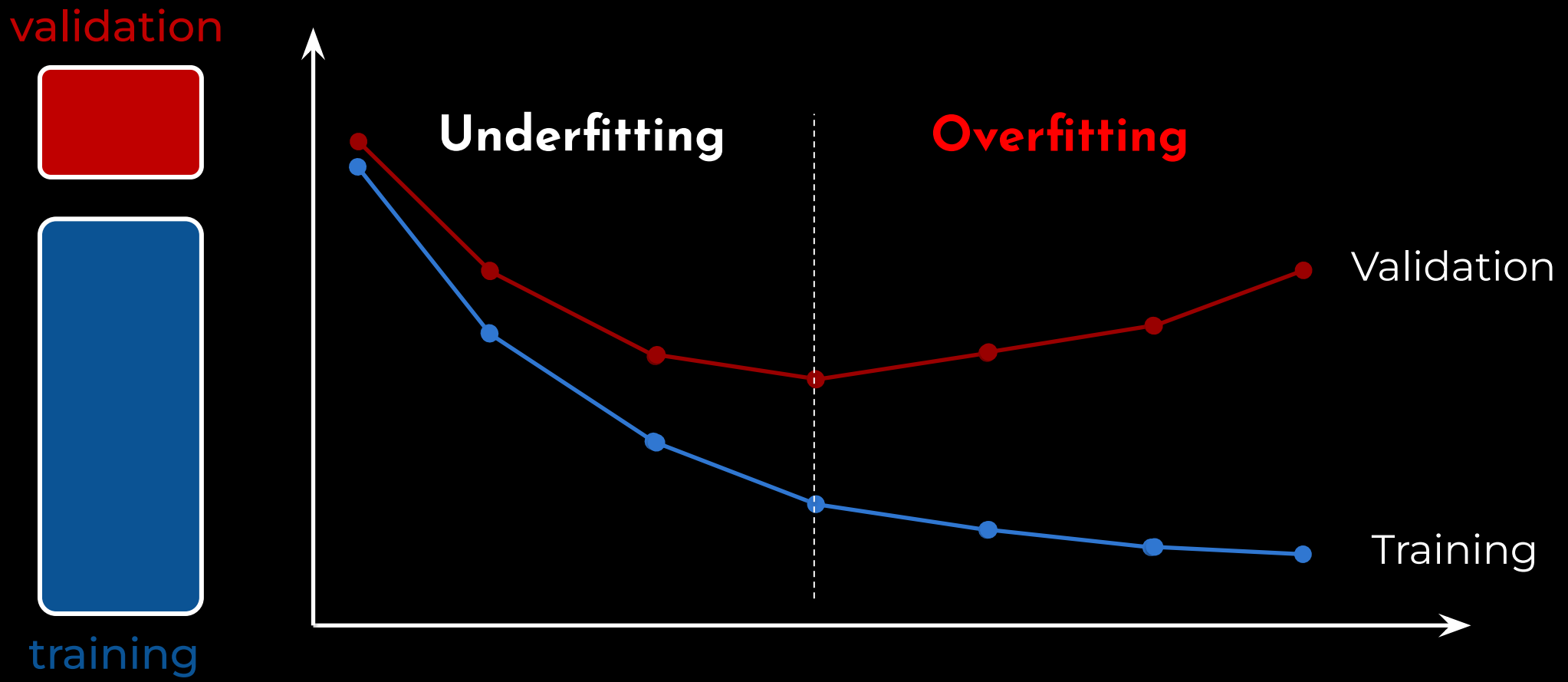
Performed on a *separate independent dataset*

Ideally this set is *out-of-distribution (o.o.d)* to prevent bias

Early stopping

Stop the learning when the error increases on the validation set

(Approximates the generalization power)

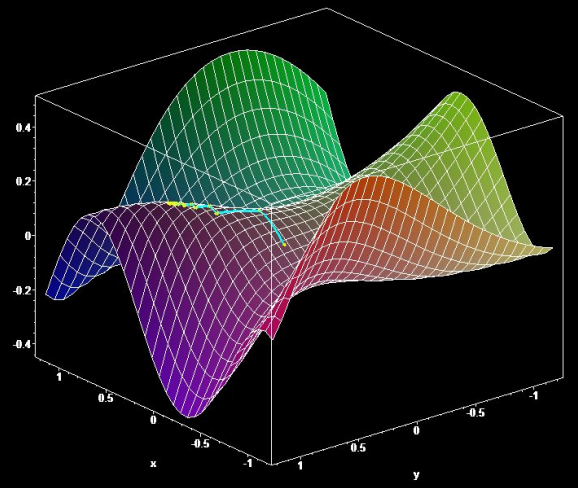


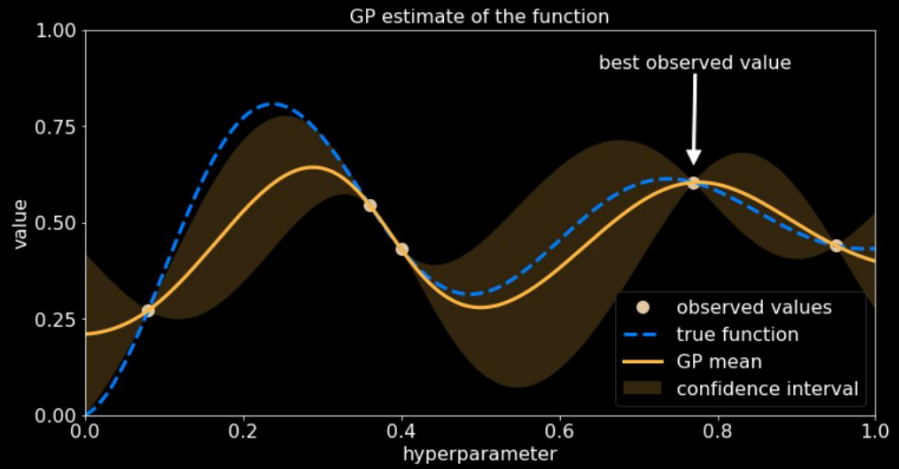
A quick note on **optimization**

Not all ML approaches use gradient descent

A wide part of the **optimization** field is centered on search

- Depth-first (lexical order) - Breadth-first
- Heuristic – genetic algorithms





- Unfortunately, we will not spend too much time on *optimization* aspects
  - This would require a course in itself !
- But still explain everything that you need to perform everything yourselves

Multiple Linear Regression

Principle Extension of simple linear regression for **two or more variables** as input
Examples: Predicting temperature based on year, CO2 gas, human population, location

Equation $f_\theta(\mathbf{x}) = \bar{y} = w_0 + w_1 x_1 + \cdots + w_m x_m \quad \theta = \{w_0, \cdots, w_m\}$

Find the best-fitting **hyperplane** still with MSE loss $\mathcal{L}_{MSE}(\bar{\mathbf{y}}, \theta) = \sum_{i=1}^{N} \left| y_i - (w_0 + \sum_{j=1}^{m} w_j x_{i,j}) \right|^2$

Matrix formulation We should compute $\nabla \mathcal{L}(\mathbf{w}) = \left[\frac{\partial \mathcal{L}}{\partial w_1}, \frac{\partial \mathcal{L}}{\partial w_2}, ..., \frac{\partial \mathcal{L}}{\partial w_m} \right]$ Deriving and updating each weight is tedious and time-consuming

This problem can be expressed in **matrix form**

$$\bar{\mathbf{y}} = \mathbf{X}\mathbf{w} + \mathbf{w}_0 \quad \mathcal{L}_{MSE}(\bar{\mathbf{y}}, \theta) = (\mathbf{y} - (\mathbf{X}\mathbf{w} + \mathbf{w}_0))$$

$$\mathbf{y} \in \mathbb{R}^{N \times 1} \quad \mathbf{w}_0 \in \mathbb{R}^{N \times 1}$$
$$\mathbf{X} \in \mathbb{R}^{N \times M} \quad \mathbf{w} \in \mathbb{R}^{M \times 1}$$

We obtain simpler expressions of the gradients $\frac{\partial \mathcal{L}}{\partial \mathbf{w}} = \mathbf{X}^T(\mathbf{y} - (\mathbf{X}\mathbf{w} + \mathbf{w}_0)) \quad \frac{\partial \mathcal{L}}{\partial \mathbf{w}_0} = (\mathbf{y} - (\mathbf{X}\mathbf{w} + \mathbf{w}_0))$

Can go further to integrate bias $\mathbf{w} = [w_1, w_2, ..., w_m, w_0] \quad \mathbf{x} = [x_1, x_2, ..., x_m, 1]$

More compact representation and efficient computation.

Linear classification

General problem

$\mathbf{x} \in \mathbb{R}^n$

Input (feature)

$\mathcal{X} \longrightarrow f_\theta \longrightarrow \mathcal{Y}$

$y \in \{0, 1\}$

Output ***class***

Find how to assign data points into distinct classes

Linearly separable problems means classes can be separated by a line

Linear classification

General problem

$\mathbf{x} \in \mathbb{R}^n$ *Input (feature)* $\quad \mathcal{X} \xrightarrow{f_\theta} \mathcal{Y}$ $\quad y \in \{0, 1\}$ *Output* ***class***

Find how to assign data points into distinct classes

Linearly separable problems means classes can be separated by a line

Approach (linear)

Use a weighted sum of input features $f_\theta(\mathbf{x}) = \mathbf{w}^T\mathbf{x} + b$

Represented in matrix form with bias term included

$\mathbf{w} = [w_1, w_2, ..., w_n, b] \quad \mathbf{x} = [x_1, x_2, ..., x_n, 1]$

Decision rule

Functions that separate classes using a linear decision boundary

$f_\theta(\mathbf{x}) \geq 0$ —— Class 0

$f_\theta(\mathbf{x}) < 0$ —— Class 1

Loss function

Hinge loss function for linear classification:

$$\mathcal{L}(\mathbf{w}, \mathbf{x}_i, y_i) = \max(0, 1 - y_i(\mathbf{w}^T\mathbf{x}_i))$$

[Exercise 1: Perform derivation and implement in NumPy]

Polynomial regression

Problem Linear models obviously only represent **linear relationships**
We are looking to increase the complexity (**capacity**) of our model

Polynomial regression $f_\theta(x) = \bar{y} = w_0 + w_1 x^1 + w_2 x^2 + \ldots + w_m x^m$

Allows to model more complex (non-linear) relationships **Note that still** $x \in \mathbb{R}$

Loss function Slightly modifying the MSE loss $\mathcal{L}_{MSE}(\bar{\mathbf{y}}, \theta) = \sum_{i=1}^{N} \left| y_i - (w_0 + \sum_{j=1}^{m} w_j x_i^j) \right|^2$

Gradient descent Actually very similar to the previous expressions $\frac{\partial \mathcal{L}}{\partial w_i}$
Remember that we are deriving with respect to

Implementation tip Prepare "higher-order features" $\mathbf{x}_{poly} = [\mathbf{x}, \mathbf{x}^2, \mathbf{x}^3, \ldots, \mathbf{x}^m]$

Regularization To prevent overfitting, add regularization $\mathcal{L}_{L_1}(\hat{\mathbf{y}}, \theta) = \mathcal{L}_{MSE}(\hat{\mathbf{y}}, \theta) + \lambda \sum_{i=1}^{m} |w_i|$

[Exercise 2: Perform derivation and implement in NumPy]

Course exercises

Exercises for this lesson and how do they differ from what we have seen together ?

General framework

1. Implement a slightly different task in NumPy
2. Produce the same implementation in JAX
3. Compare both versions

1 - Linear classification

Identical model form and setup as linear regression

Major difference: loss function (and domain)

$$y \in \{0, 1\}$$

$$\mathcal{L}(\mathbf{w}, \mathbf{x}_i, y_i) = \max(0, 1 - y_i(\mathbf{w}^T \mathbf{x}_i))$$

2 - Polynomial regression

Identical task and setup as linear regression

Major difference: model used

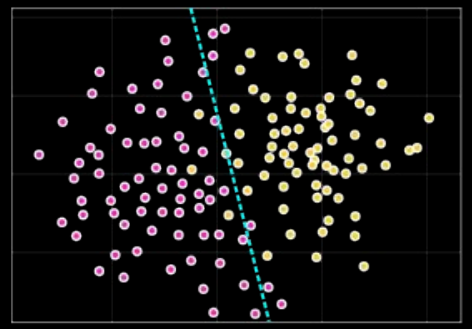
$$f_\theta(x) = \bar{y} = w_0 + w_1 x^1 + w_2 x^2 + ... + w_m x^m$$

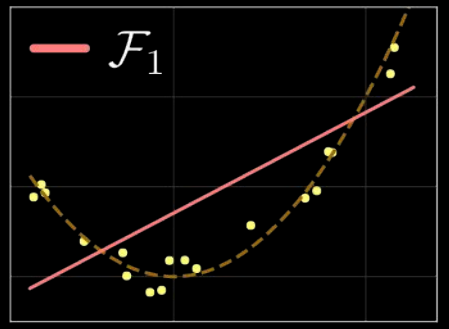
Also no base code for this exercise (learn to define it yourself)

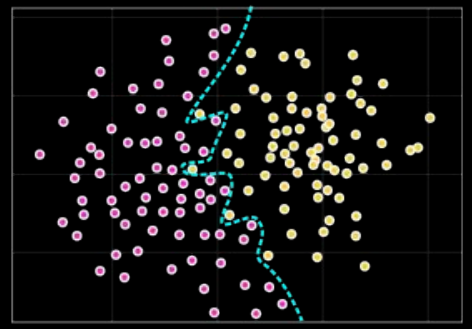
Understanding capacity

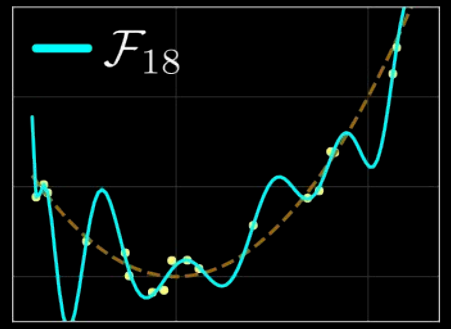
Classification

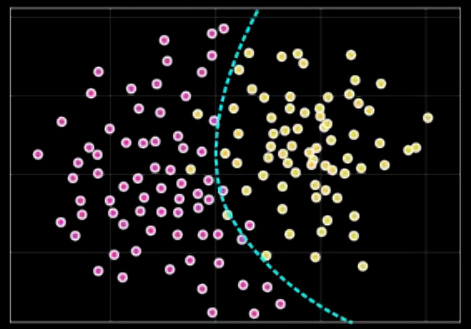
Regression

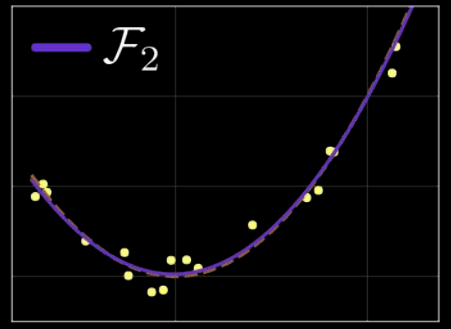












Underfitting

- Function family is **too poor**
- Capacity is **too low** for this problem

Overfitting

- Function family is **too rich**
- Capacity is **too high** for this problem

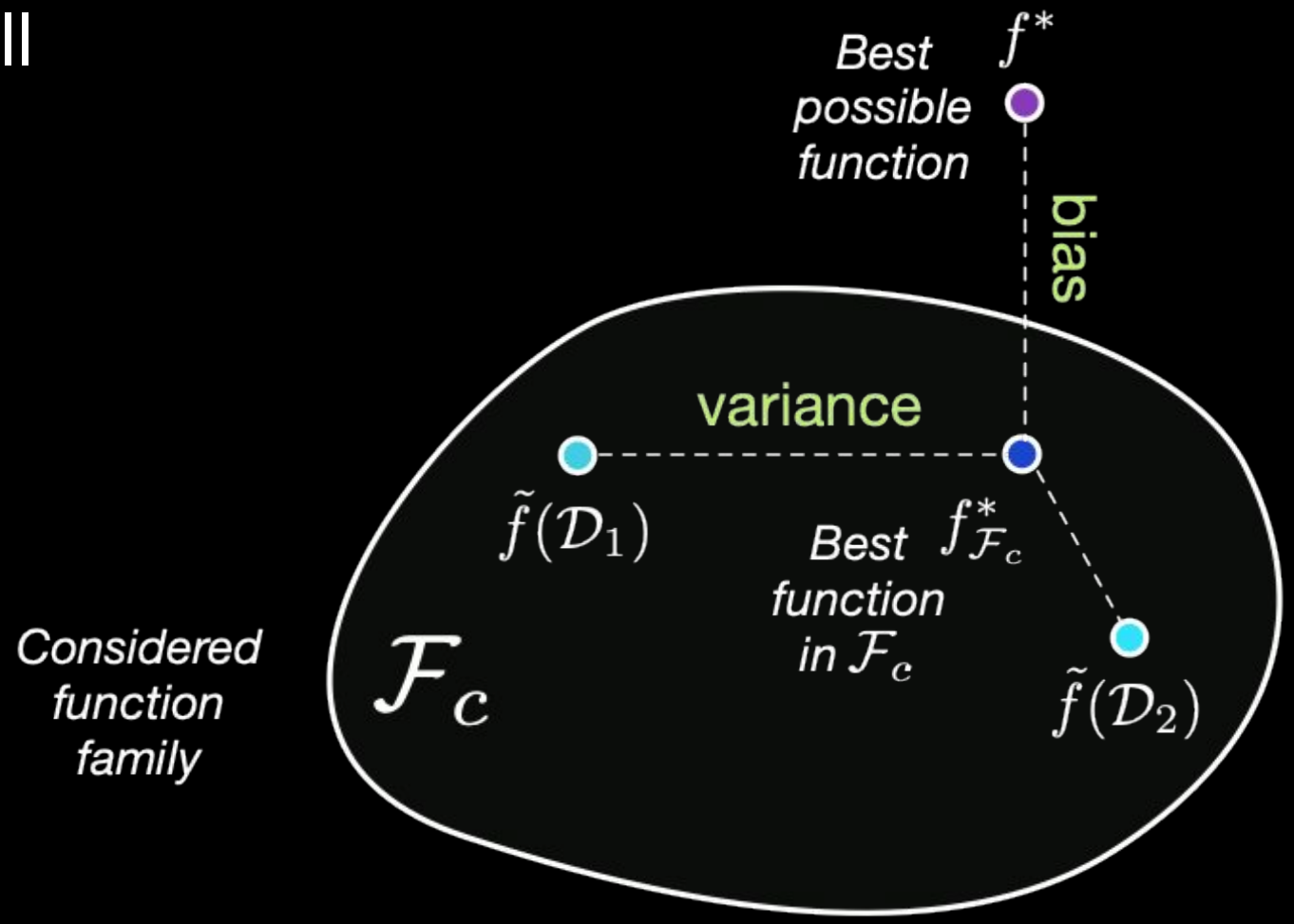
Optimal capacity

- Function family is **adequate**
- **Optimal capacity** for this problem

Bias and variance decomposition

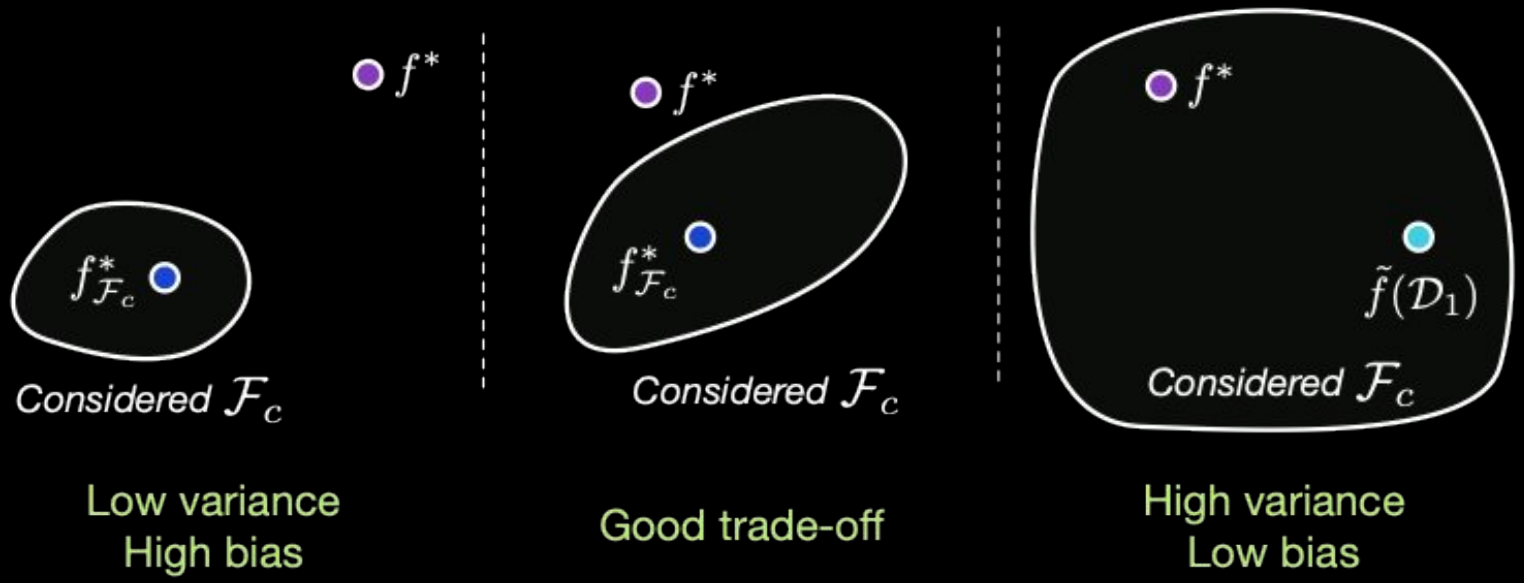
This problem lies in the bias and variance of our approximation

Space of all possible functions



Bias and variance - details

So how can we adequately choose the family ?



Problem in the variance aspect is the discrepancy lying between

Expected risk
(what we want)

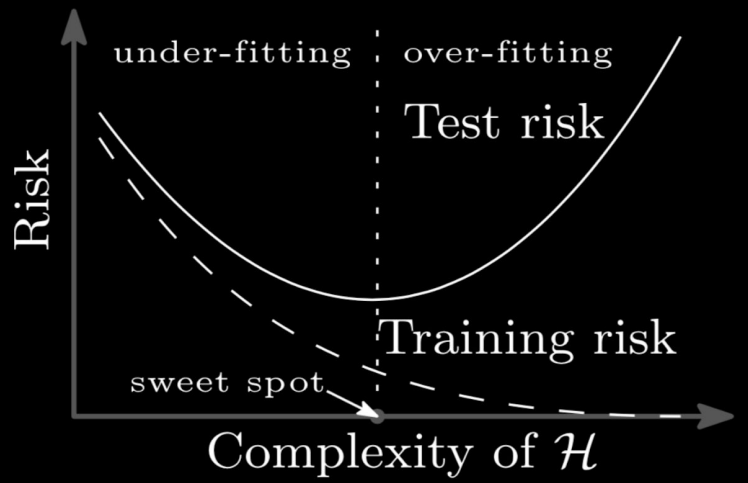
$$\mathcal{R}\left(f_\theta\right) = \mathbb{E}_{(\mathbf{x},\mathbf{y})\sim p(\mathbf{x},\mathbf{y})}\left[\mathcal{L}\left(f_\theta(\mathbf{x}), \mathbf{y}\right)\right]$$

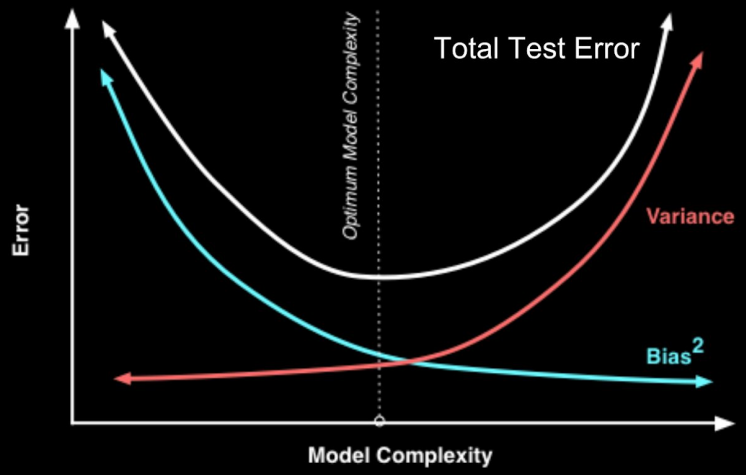
Empirical risk
(what we have)

$$\hat{\mathcal{R}}\left(f_\theta, \mathcal{D}\right) = \frac{1}{|\mathcal{D}|}\sum_{(\mathbf{x},\mathbf{y})\in\mathcal{D}} \mathcal{L}(f_\theta(\mathbf{x}), \mathbf{y})$$

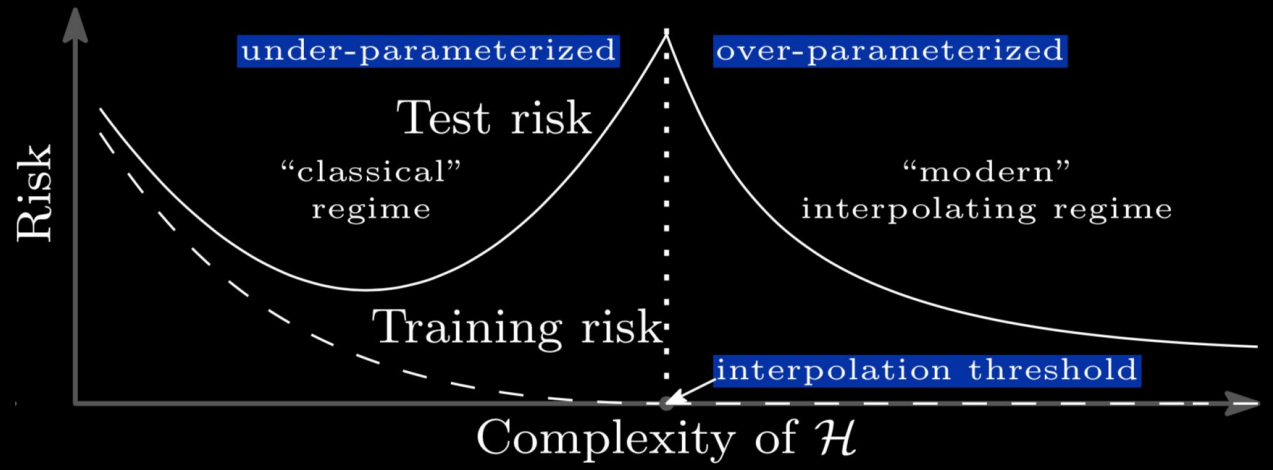
Modern risk curves for deep learning

We used to think about **overfitting** (risk curves)





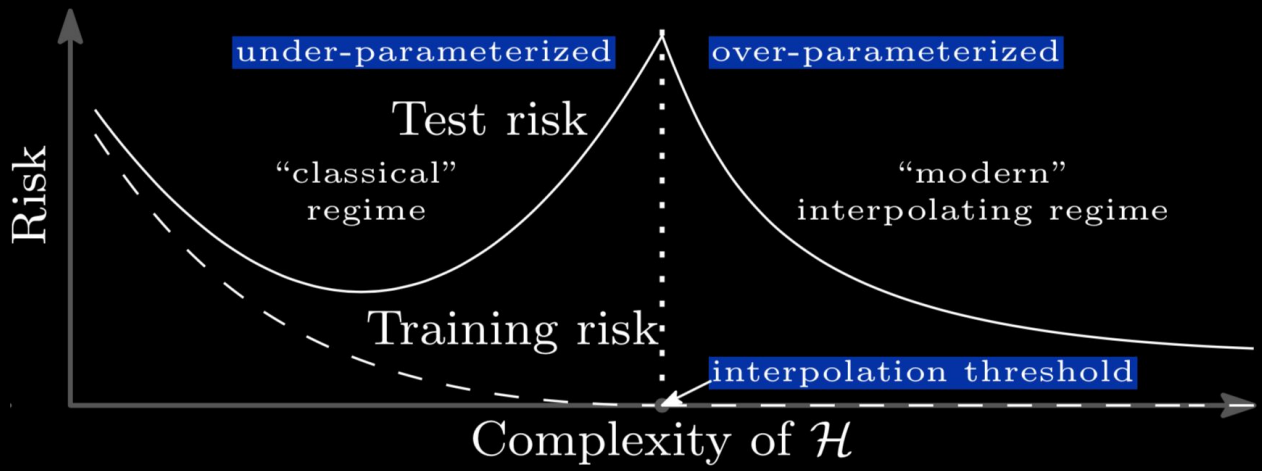
But **overparameterized** models have an **entirely different behavior**



[Belkin, et al (2019). *Reconciling modern machine-learning practice and the classical bias-variance trade-off.*. PNAS, 116(32).]

Modern risk curves for deep learning

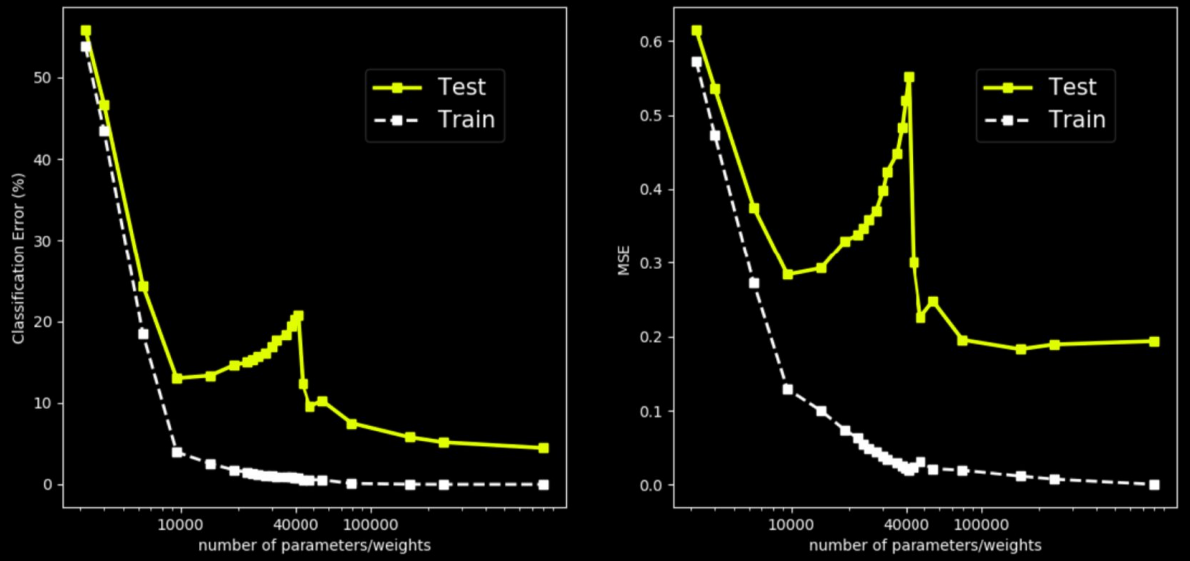
This idealized curve can be validated



Experimental validation

MNIST dataset

Clear regime difference



[Belkin, et al (2019). *Reconciling modern machine-learning practice and the classical bias-variance trade-off.*. PNAS, 116(32).]

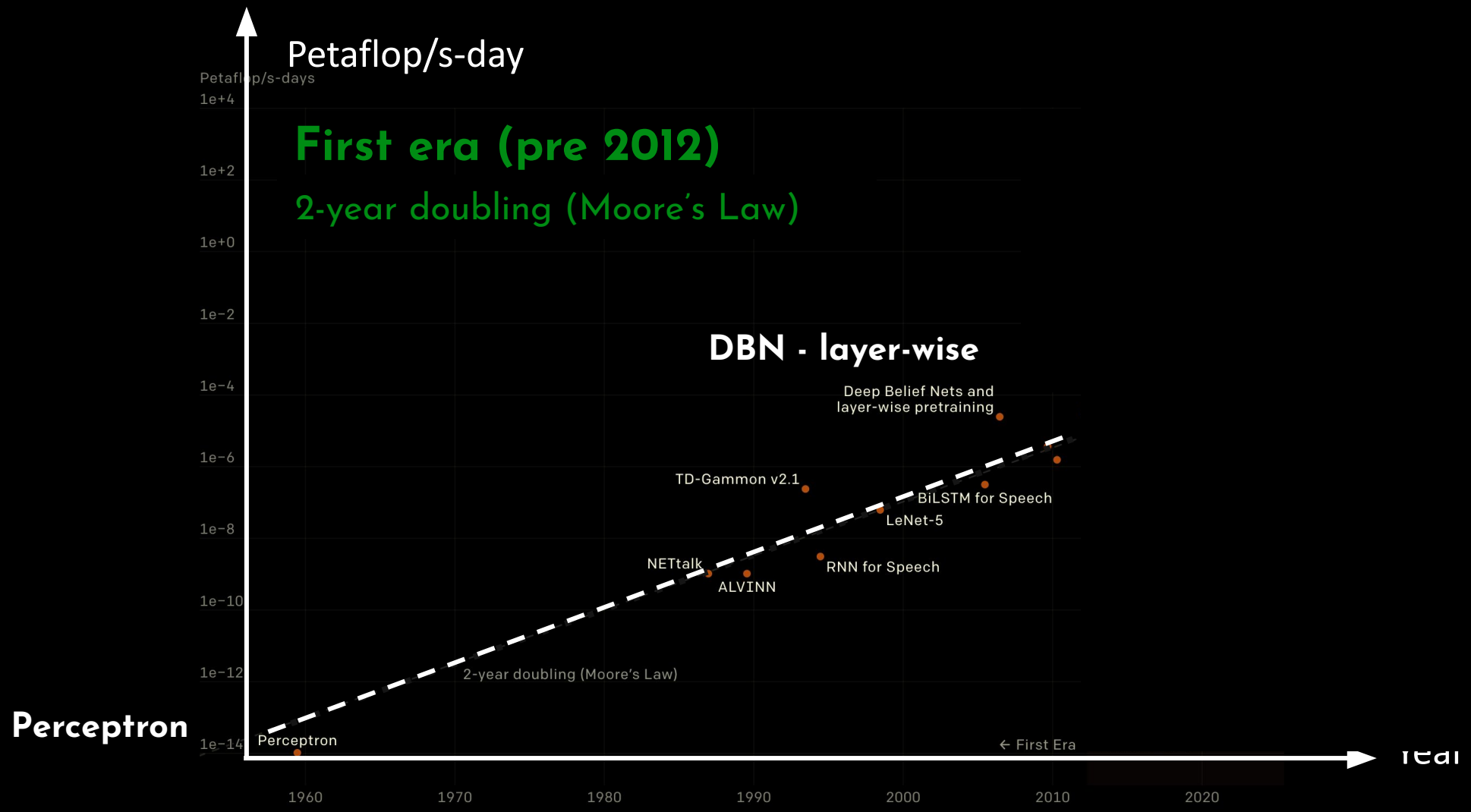
Scaling laws and data

How data naturally regularizes complexity

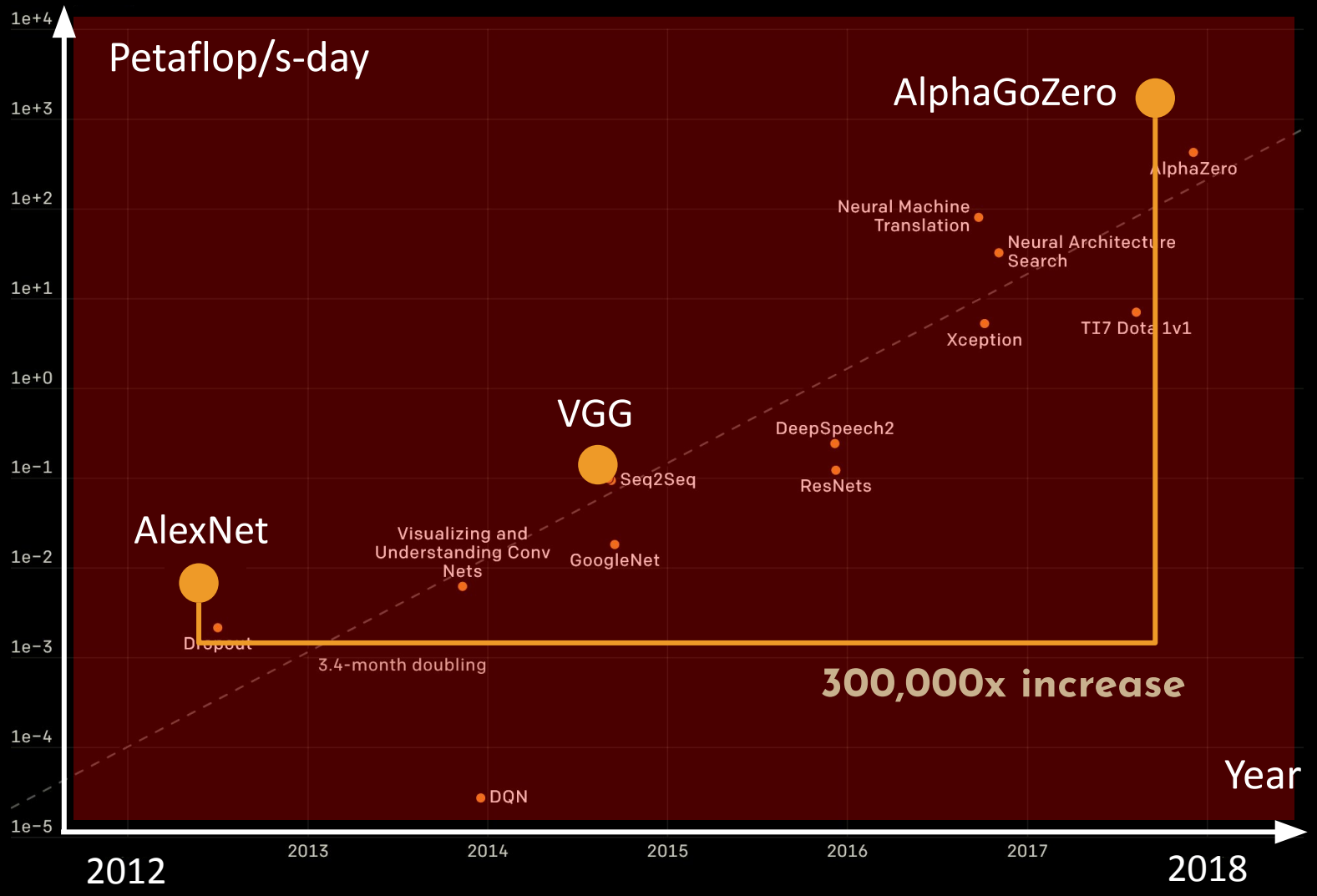
Eras in machine learning

Two distinct eras in ML

Dario Amodei and Danny Hernandez. AI and compute (2018)



Eras in machine learning (zooming in)



Dario Amodei and Danny Hernandez. AI and compute (2018)

Consequences and observations

Direct consequences of this accuracy race

- **Huge environmental issues**
- **Precludes the use in non-specialized (user-side) hardware**
- **Even less possible to embed such systems**

***175 billon parameters, t**akes 355 years on a single GPU to train*

GPT-3

Carbon footprint for training equivalent to driving to the moon and back [3]

Dr. James O'Donoghue using NASA imagery.

Observation #2 - Occam's razor and complexity

The well-known Occam's razor principle

« Entities should not be multiplied without necessity. »

Or equivalently …

« The simplest explanation is most likely the right one »

More formal view is the Minimum Description Length (MDL) principle

« Comprehension is compression »

Given a set of models $\mathcal{H}_1, \cdots, \mathcal{H}_n$ that can explain the dataset $\mathcal{D}$

The MDL principle states that

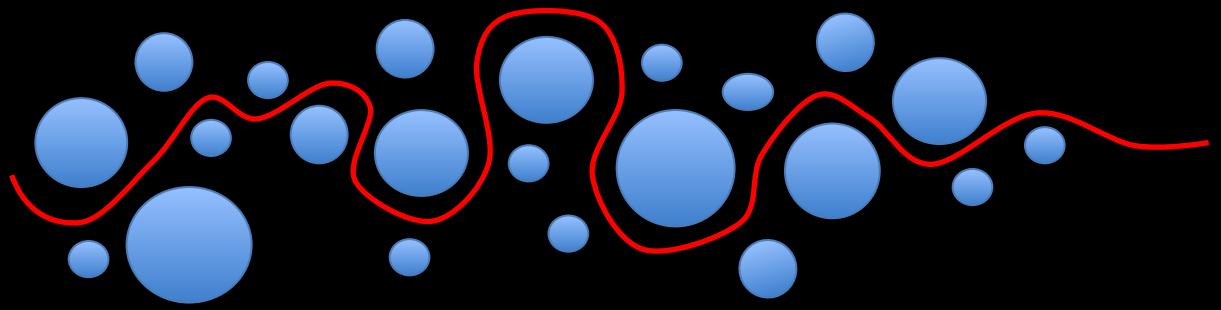
$$\mathcal{H}^{best} = \underset{\mathcal{H}}{\operatorname{argmin}} \left[L(\mathcal{H}) + L(\mathcal{D}|\mathcal{H}) \right]$$

$L(\mathcal{H})$: Length of the description of model $\mathcal{H}$ in bits

$L(\mathcal{D}|\mathcal{H})$: Length of describing data $\mathcal{D}$ encoded by model $\mathcal{H}$ in bits

Observation #1 - Complexity of the problem

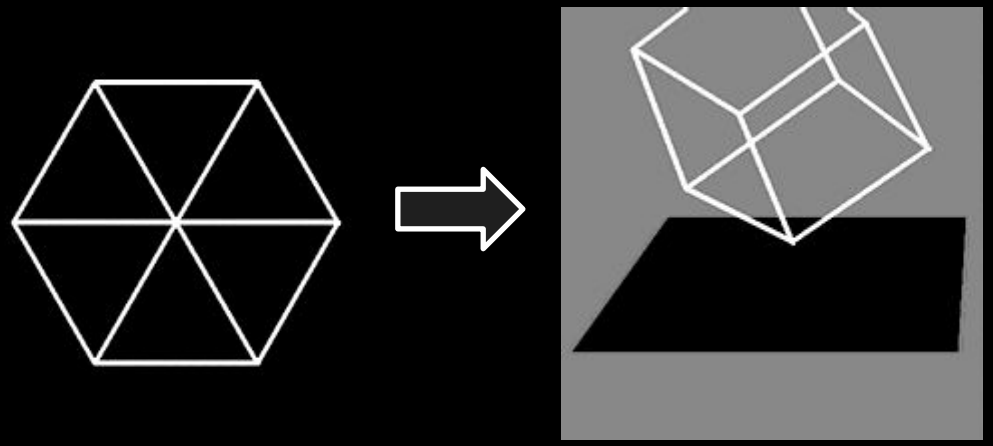
Imagine you observe the path of an ant



Seems complicated ... you could say the ant is extremely smart
You look closer, there are rocks that the ant is just avoiding

Complexity can be consequence of the environment not the program

Now imagine you are trying to understand this behavior

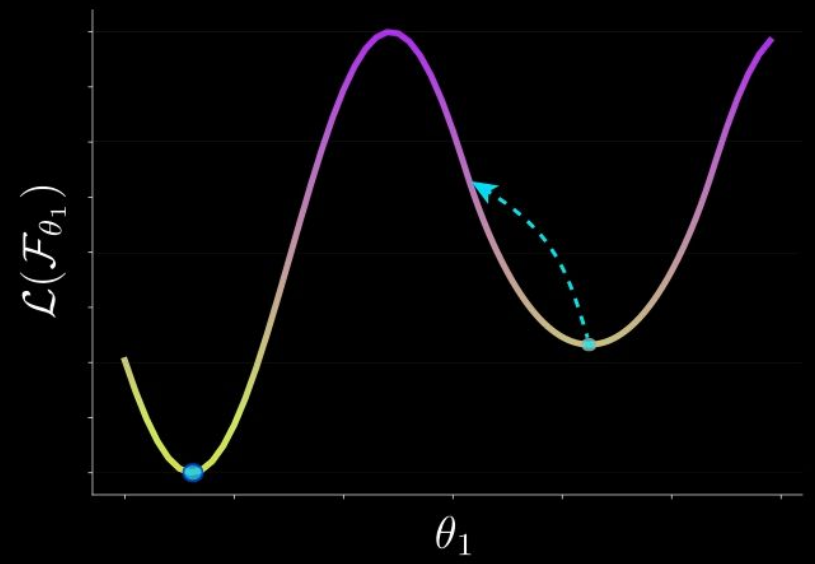


Notion of problem dimensionality

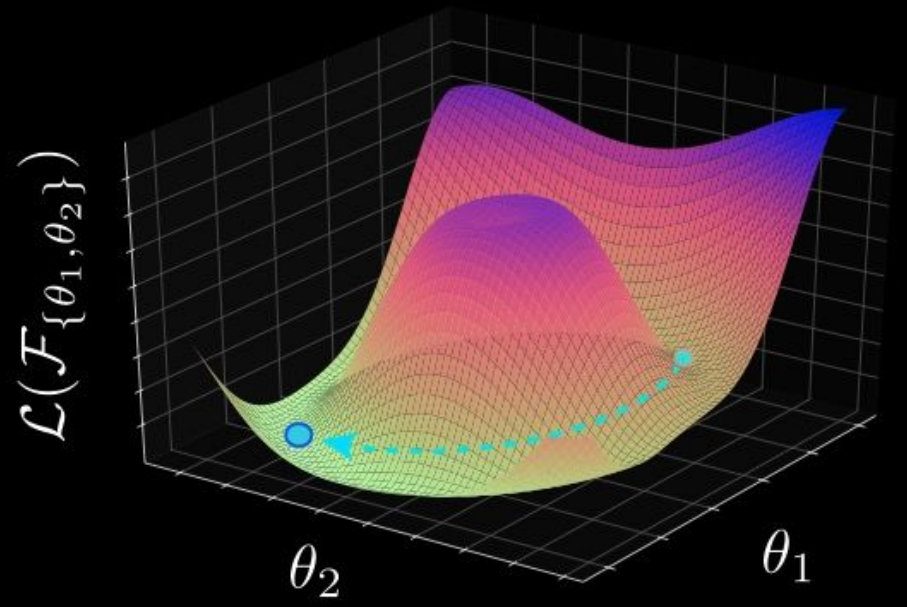
Overparametrization

One potential explanation on why overparameterization works

Imagine the loss landscape (error given parameter values)



With a single parameter, hard to escape minima



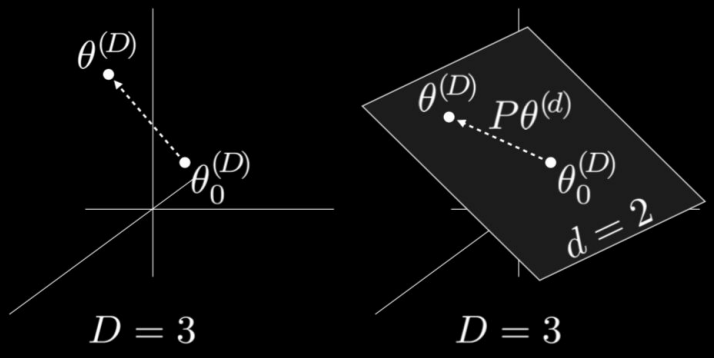
Extra parameter, we can « go around » (idealized)

Overparametrization **simplifies the training …** allowing to find a **better solution faster**

Does not mean that the final solution *needs* all these parameters

Intriguing perspectives for understanding

Mode connectivity

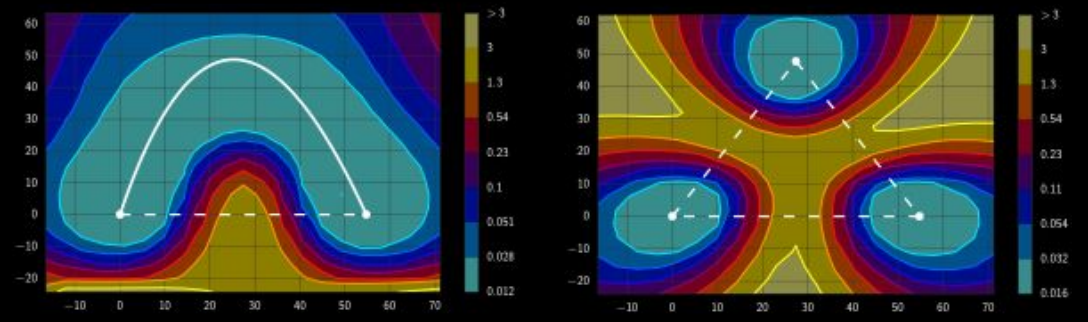


Mode (efficient solutions) connectivity

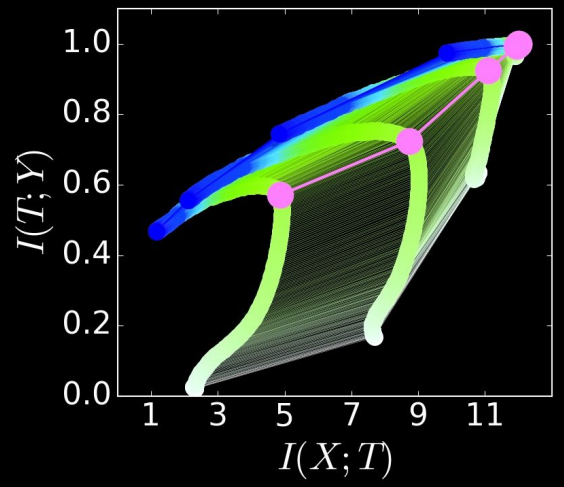
How loss surfaces have « valleys »

Efficient solutions might live on a subspace

Hence, we could simplify the models



Garipov, et al. (2018). Loss surfaces, mode connectivity, and fast ensembling of dnns. In Advances in Neural Information Processing Systems (pp. 8789-8798).



Information Bottleneck theory

Two distinct period in training

- First one maximizes *mutual information*
- Second one performs compression

Shwartz-Ziv, R., & Tishby, N. (2017). Opening the black box of deep neural networks via information. arXiv preprint arXiv:1703.00810.

Recalling our program

3 major types of learning

- **Supervised learning** is inferring a function from labeled training data
- **Unsupervised learning** is trying to find hidden structure in unlabeled data
- **Reinforcement learning** is acting to maximize a notion of cumulative reward

Self-supervised learning is using the data itself directly to define tasks to solve

Detailed program

Supervised (discriminative)

Unsupervised (generative)

1. Introduction
2. Machine learning
3. Neural networks
4. Advanced networks
5. Deep learning
6. Probabilities and Bayesian inference
7. Latent models, EM and GMM
8. Approximate inference
9. Variational Auto-Encoders (VAEs) and flows
10. Adversarial learning (GANs)
11. Diffusion models

Working with creative data (music)

Real-world applications of this course

- Up to now we have talked on an abstract level
- We observe relationships between $\mathcal{X}$ and $\mathcal{Y}$

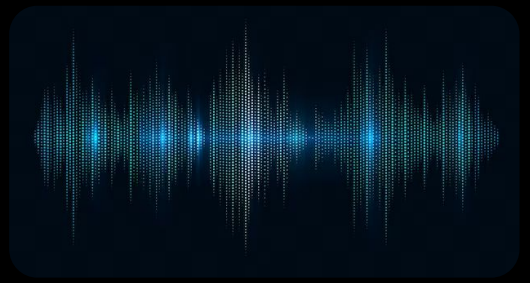
So what is the *nature* of this $\mathcal{X}$?

This is defined by the **nature of the *observations***

Nature of audio observations

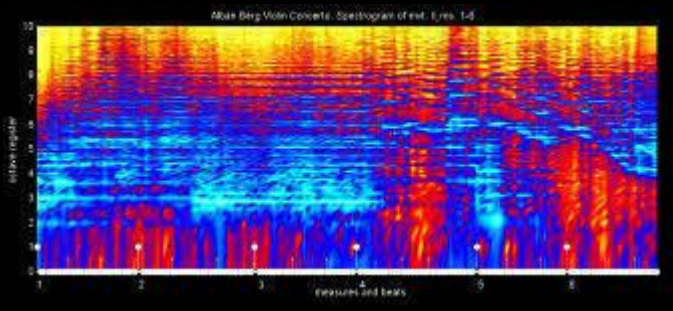
The major problem is the ***dimensionality*** of audio observations
In the case of waveform audio data, this problem is huge

raw waveform



5 seconds of 44.1k audio
220,500 dimensions

spectral transform



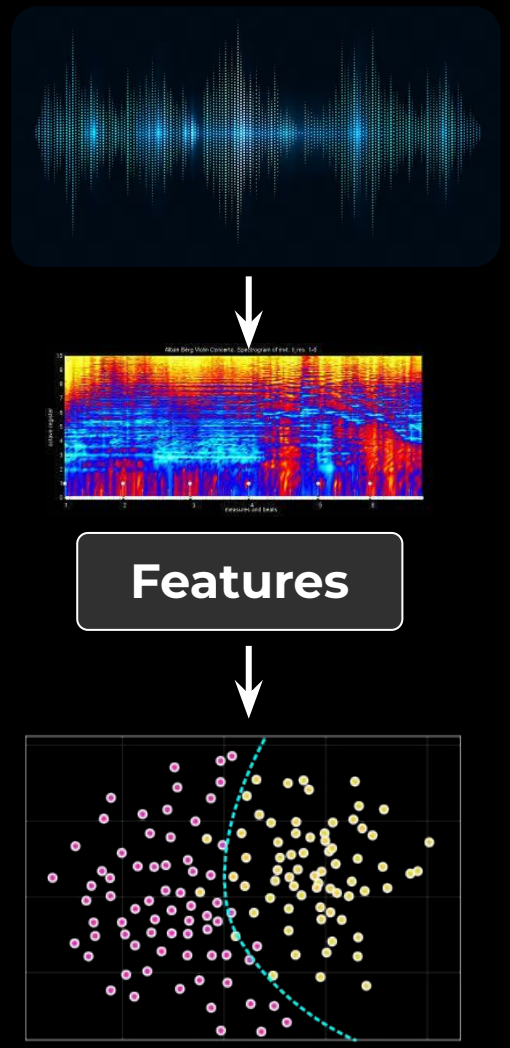
2048 bands for 512 steps
220,500 dimensions

known features

- *Pitch*
- *Loudness*
- *Centroid*

Seminal approach of
feature-based learning

Feature-based learning



Typical workflow prior to deep learning

How to define a well-optimizable problem

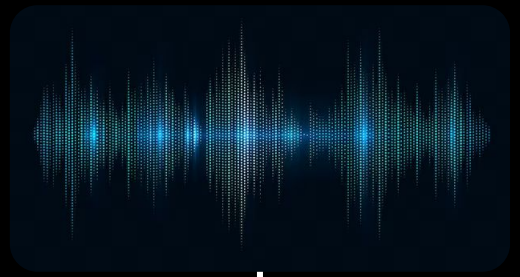
- First (pre-)process and normalize the observations
- Extract some features highly relevant to the problem
  - Highly problem-dependent
- Set of high-level features still associated to our classes
- Allows to use our simple learning algorithms

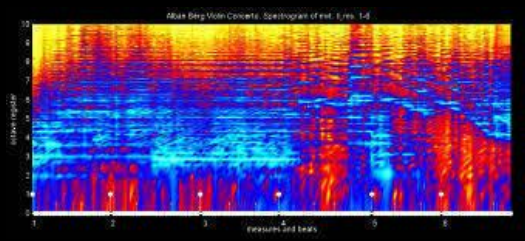
Which features to use ?

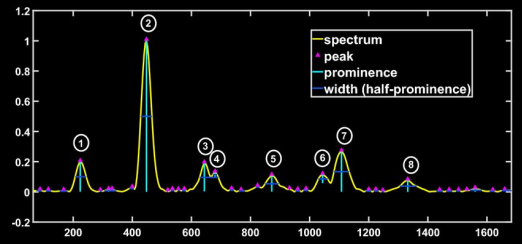
- Highly depends on the task at hand !
- Years of research on audio features

Audio features

Large available set of features to compute







Signal

Frames

Spectral

Sinusoidal

Perceptual

Instantaneous signal descriptors

- Energy envelope (RMS)
- Zero-crossing rate (Noisiness)
- Auto-correlation (pitch)

Spectral transforms

- Mel-spectrogram
- Constant-Q transform
- Mel Frequency Cepstral Coefficients (MFCC)

Harmonic descriptors

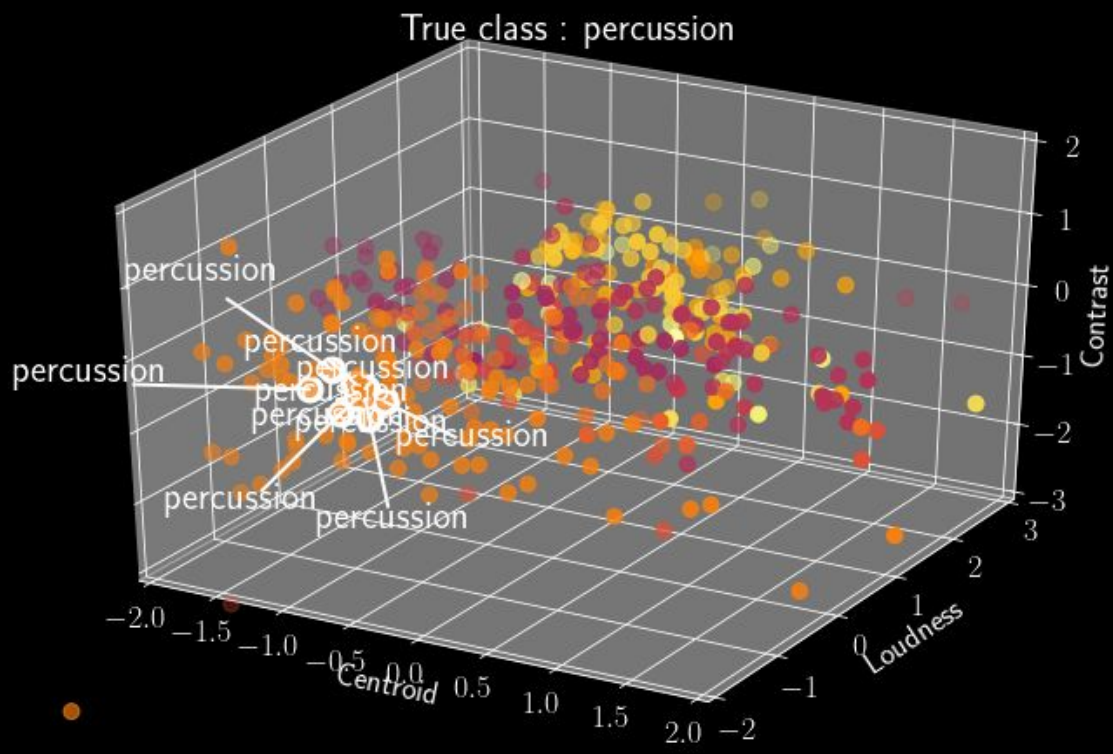
- Energy envelope (RMS)
- Zero-crossing rate (Noisiness)
- Auto-correlation (pitch)

Perceptual descriptors

- Energy envelope (RMS)
- Zero-crossing rate (Noisiness)
- Auto-correlation (pitch)

Feature-based learning

Typical audio feature spaces already provide interesting separation



- *Similar examples are usually grouped*
- Naïve way of adressing our classification = *look at neighbors*