Applied Deep Learning

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Learning objectives of today

Goals: Be ready for your group assignment

How will we do this?

- We will learn and practice another way to tune hyperparameters
- Then, we will take a look at autoencoders, a specific type of neural network
- Finally, we will discuss the case underlying the assignment, as well as some of the key challenges

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Hyperparameter tuning with Keras tuner

Let’s try it together in Python

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Hyperparameter tuning process with Keras Tuner

1. Define a function that, given a hyperparameter-setter, creates a model
   - Within that function, using the hyperparameter-setter, we define the hyperparameter space

2. Define an instance of the Keras Tuner, specifying the type of hyperparameter search
   - Can use RandomSearch, Hyperband, Sklearn, BayesianOptimization

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3. Let the tuner do its magic
   The hyperparameter-setter will automatically choose the “correct” hyperparameters

4. Based on the best parameters found, generate a model, train it, and evaluate it

5. Look at the outcome, possibly search in a smaller grid

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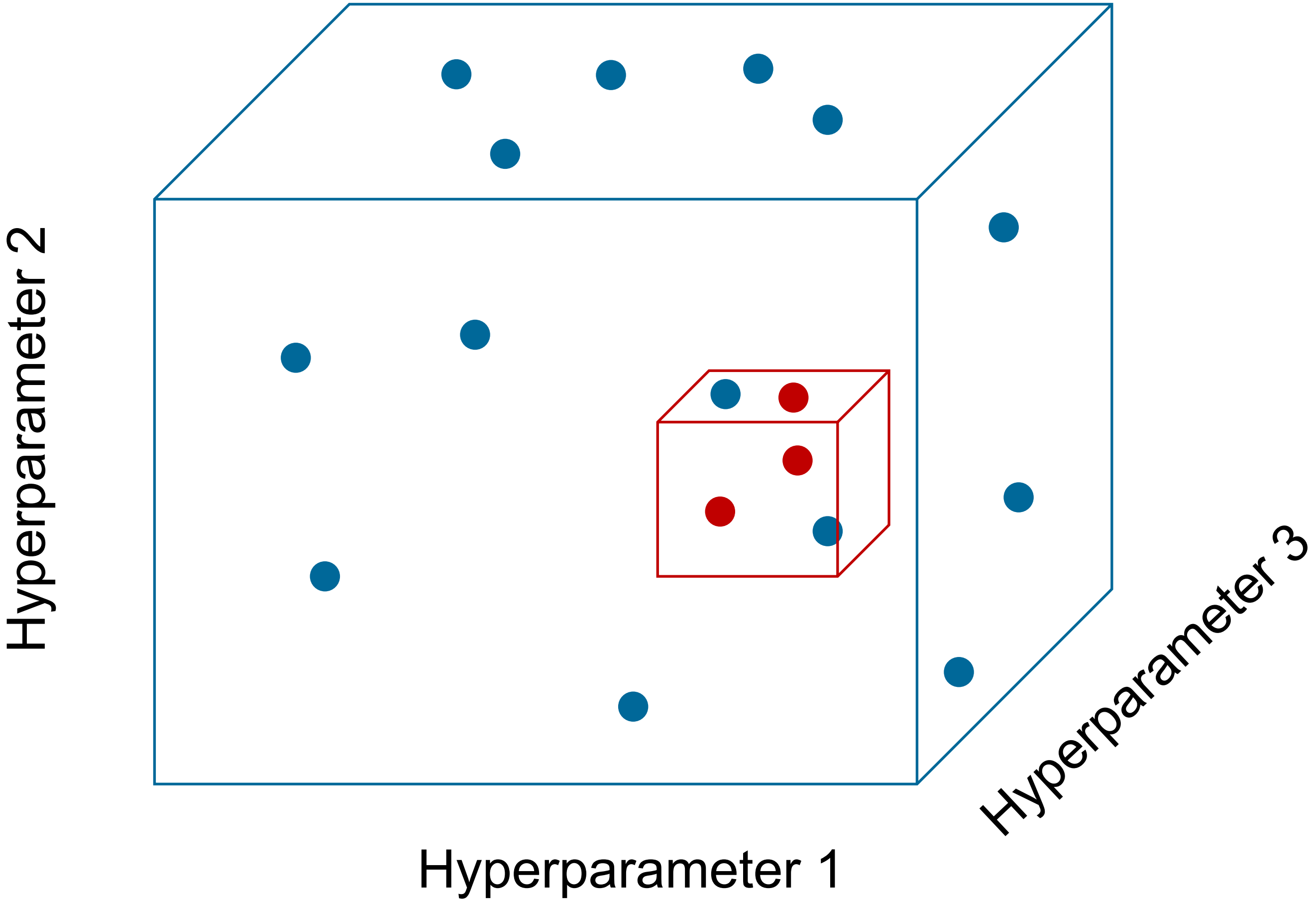
Hyperparameter space



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Autoencoders

What is an autoencoder?

- A neural network that predicts its own inputs
  → So that we can learn a (compact) representation of the data

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Recall that a neural network learns representations

x

Learn $f(\cdot)$

$f(x)$

Learn $\mathrm{g}(\cdot)$

$g\big(f(x)\big) \approx y$

E.g., $y = 1$, if it's a cat
$y = 0$, if it's a BA student

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Recall that a neural network learns representations

x

Learn $f(\cdot)$

$f(x)$

Learn $\mathrm{g}(\cdot)$

$g(f(x)) \approx x$

Why do we want to “copy” the input?

- We don’t care about the copy itself (which should be good, nevertheless)
- What we care about is a (compact) representation of the data, $f(x)$ that is good enough to recreate x

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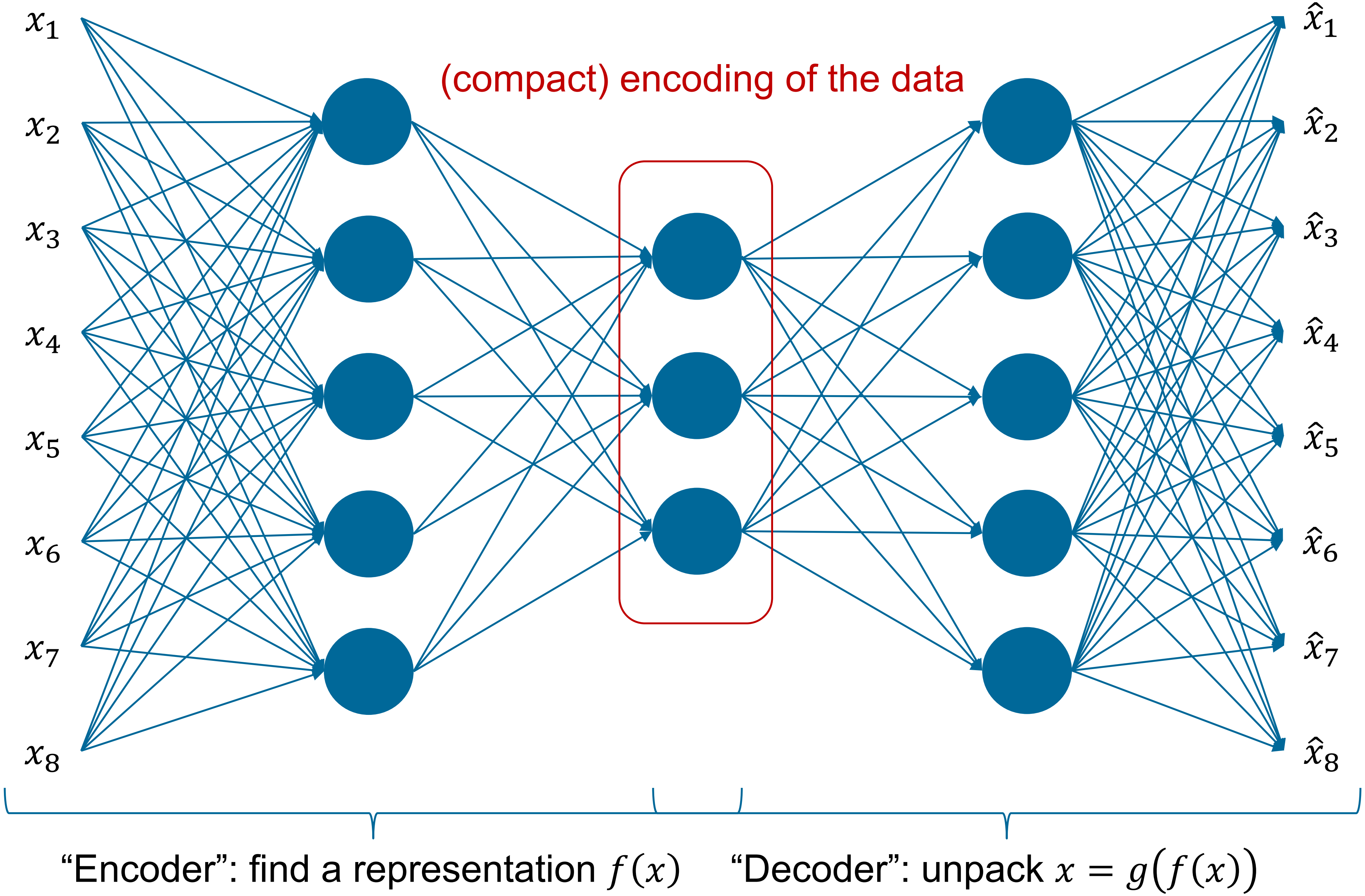
The structure of an autoencoder



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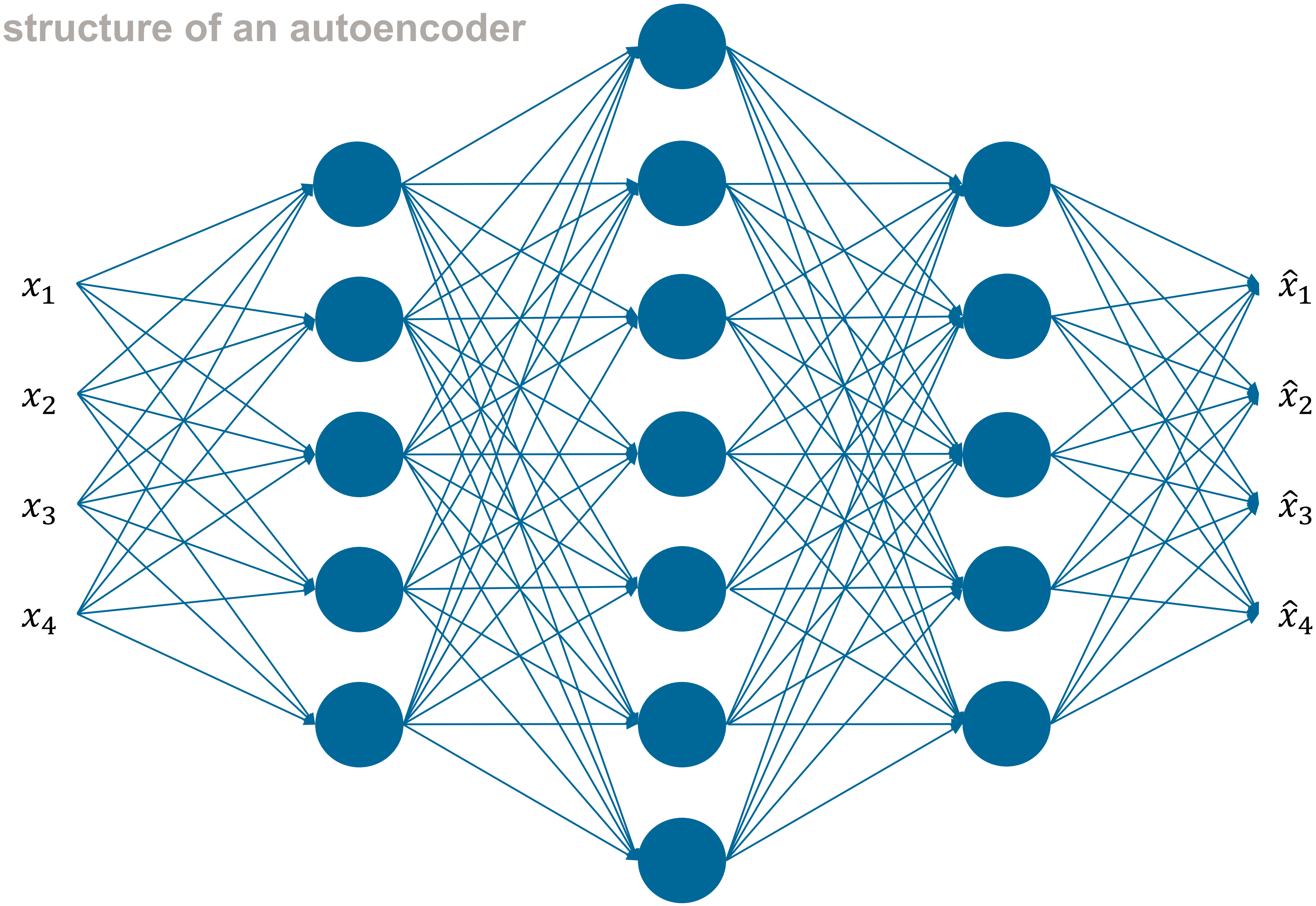
NOT the structure of an autoencoder



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What to use it for?

- Dimensionality reduction ("advanced PCA")
- **Denoising: train to "recover" non-noisy data from noisy data**

- Anomaly detection: train to represent normal data. When data cannot be predicted well, it is likely to be "anormal"
- Generate new content (such as images): variational autoencoders

The process for denoising

- We create artificial noise on our data

- We build an autoencoder that takes the noisy data as input, and tries to build an accurate representation of the original
  - To do so with images, we need convolutional layers. Don't worry about how they work, we will get to them soon. You find all the code on using them in the notebook!
  - Training the autoencoder may take quite a bit of time! (I suggest first getting to the training part, then taking a break in the meantime)

- We then can run the autoencoder on new (noisy) data, to create non-noisy versions

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Try it out in Python

An overview of the group assignment

The group assignment

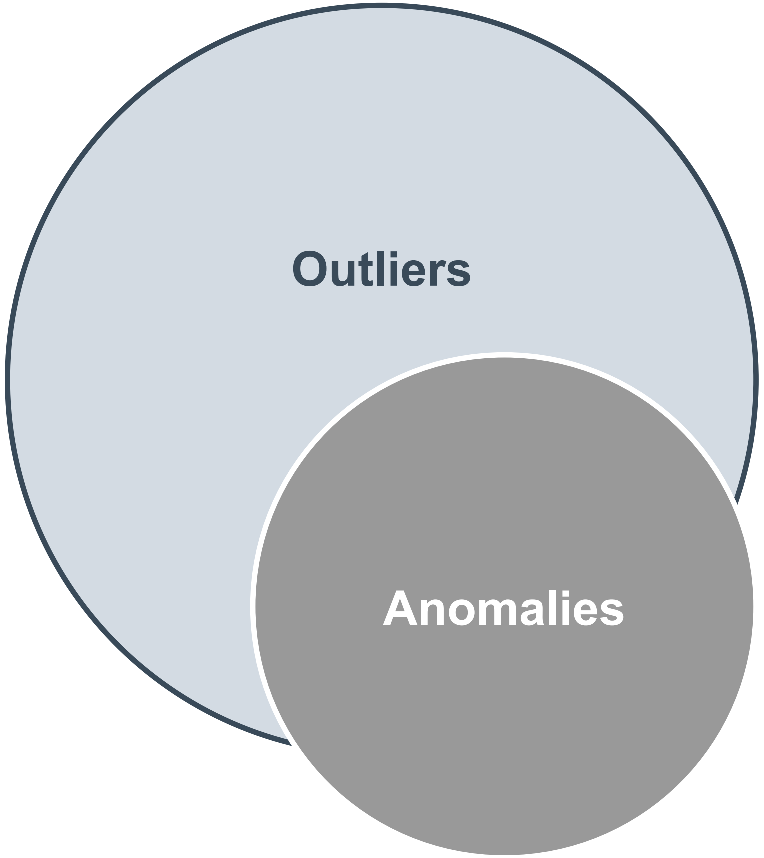
- "To Catch a Thief": A case about "Shift", an InsureTech startup that helps insurance companies uncover fraudulent claims
  - In particular, their algorithm flags suspicious cases for claim handlers to investigate

- We have a dataset of vehicle insurance claims. One issues is that it is "unbalanced"
  → only about 1% of cases are frauds
  → What would be the accuracy of an algorithm that always predicts "no fraud"?

- Your tasks:
  - Pre-processing
  - Understanding the relevant metrics
  - Trialing and comparing models of varying complexity
  - Exploring autoencoders as a tool to detect anormal data
  - Discussing transparency implications of neural networks

Anomaly detection with autoencoders

Outliers and anomalies



Outliers:

- Data points that are distinctly different from other data points
- Can be caused by unavoidable random errors or by systematic errors relating to how data was sampled

Anomalies:

- Outliers or other values that are not expected to exist
- Can be context- or pattern-based:
    - Context: exceptionally high credit card spending on Black Friday versus near-simultaneous spending in New York and London
    - Pattern: high credit card spending every Saturday versus high spending on a day where spending is low in other weeks

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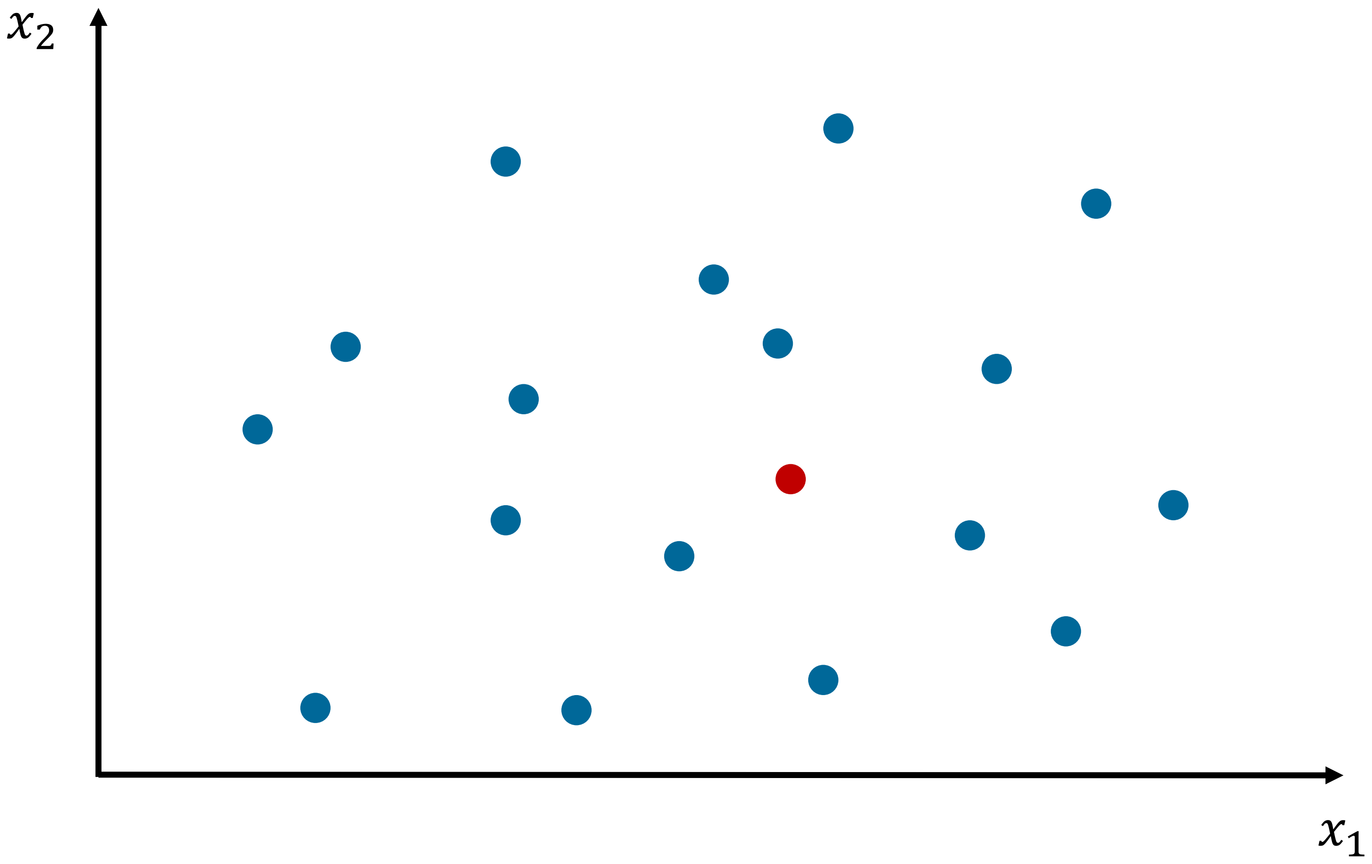
Differentiating anomalies from normal observations



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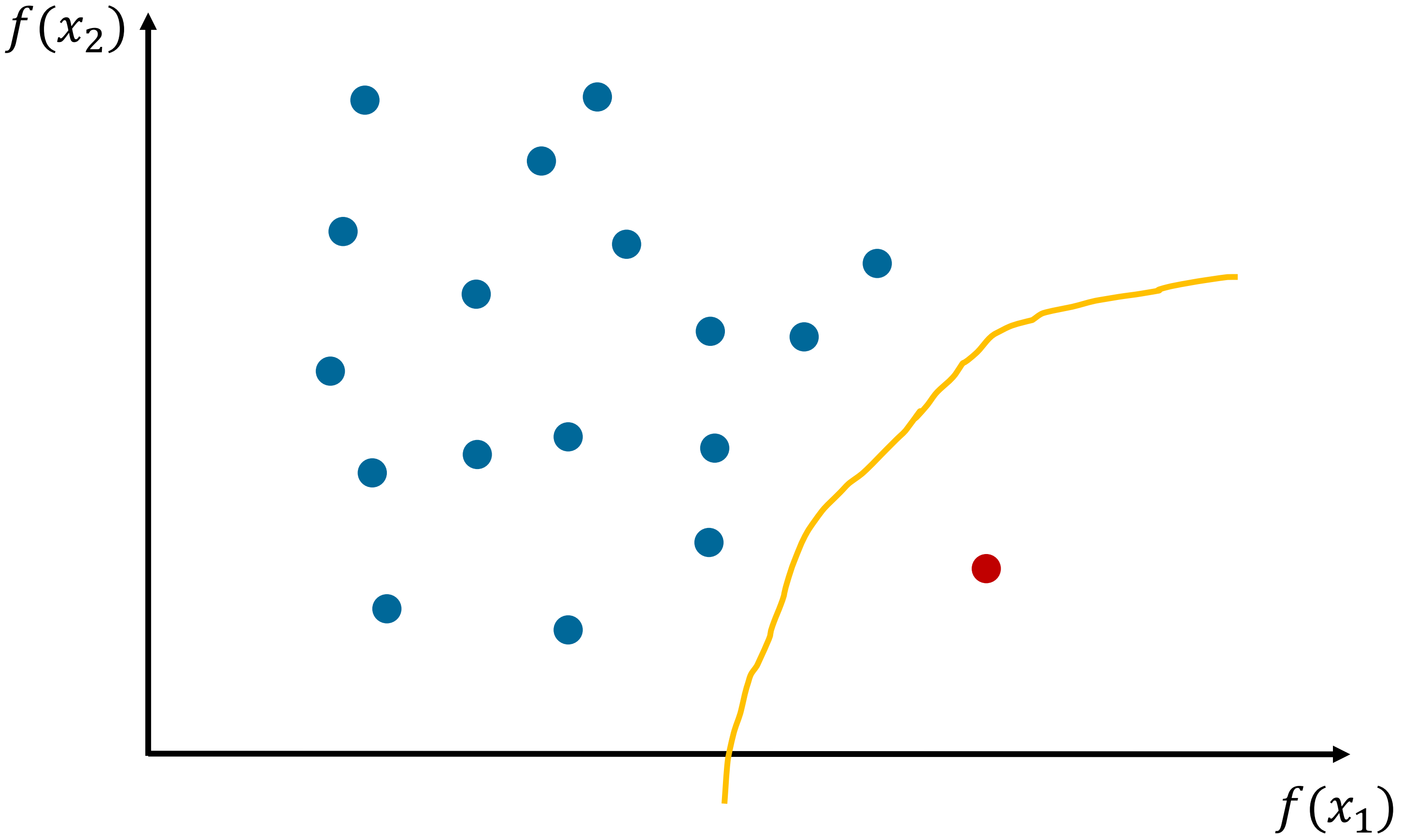
Differentiating anomalies from normal observations



What are possible anomalies and how would we detect them?

Consider the following situations:

- A machine produces thousands of screws per minute, every few days the type of screw is changed
- A software developer for a bank downloads a large number of entries from a customer database
- An intermediary supplies fair trade coffee beans

What is the expected outcome in each case?

What is an anomalous outcome?

What data do we observe?

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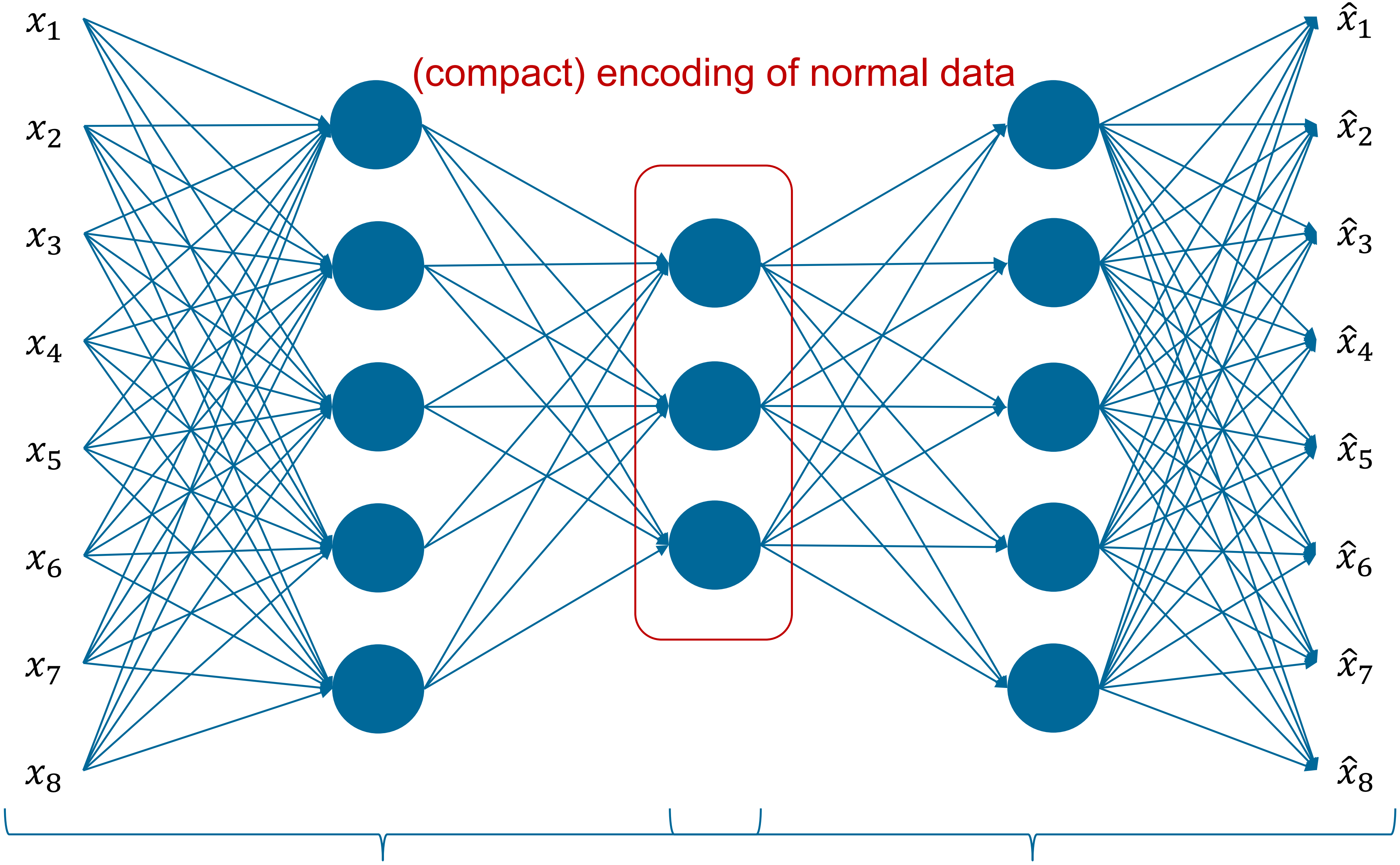
Detecting anomalies

Supervised anomaly detection:
- A fancy way of saying classification – learn to differentiate between two classes
- We can use the standard toolbox
- When feasible, usually the most failsafe method
- Only works if we know how anormal data looks like, i.e., we have enough data points

Semi-supervised anomaly detection:
- Learn an efficient representation of normal data and then try to apply this to new data coming in
- We can use autoencoders and other tools
- We don't need to know how anormal data looks like
- Still need to be sure that our normal data is actually normal

Unsupervised anomaly detection:
- Learn "how far" datapoints are from each other and recognize the ones that are far away from anything else
- We can use isolation forests and other tools
- We can work with any kind of data
- We don't have many guarantees

Anomaly detection with an autoencoder



"Encoder": find a representation $f(x)$ "Decoder": unpack $x = g(f(x))$

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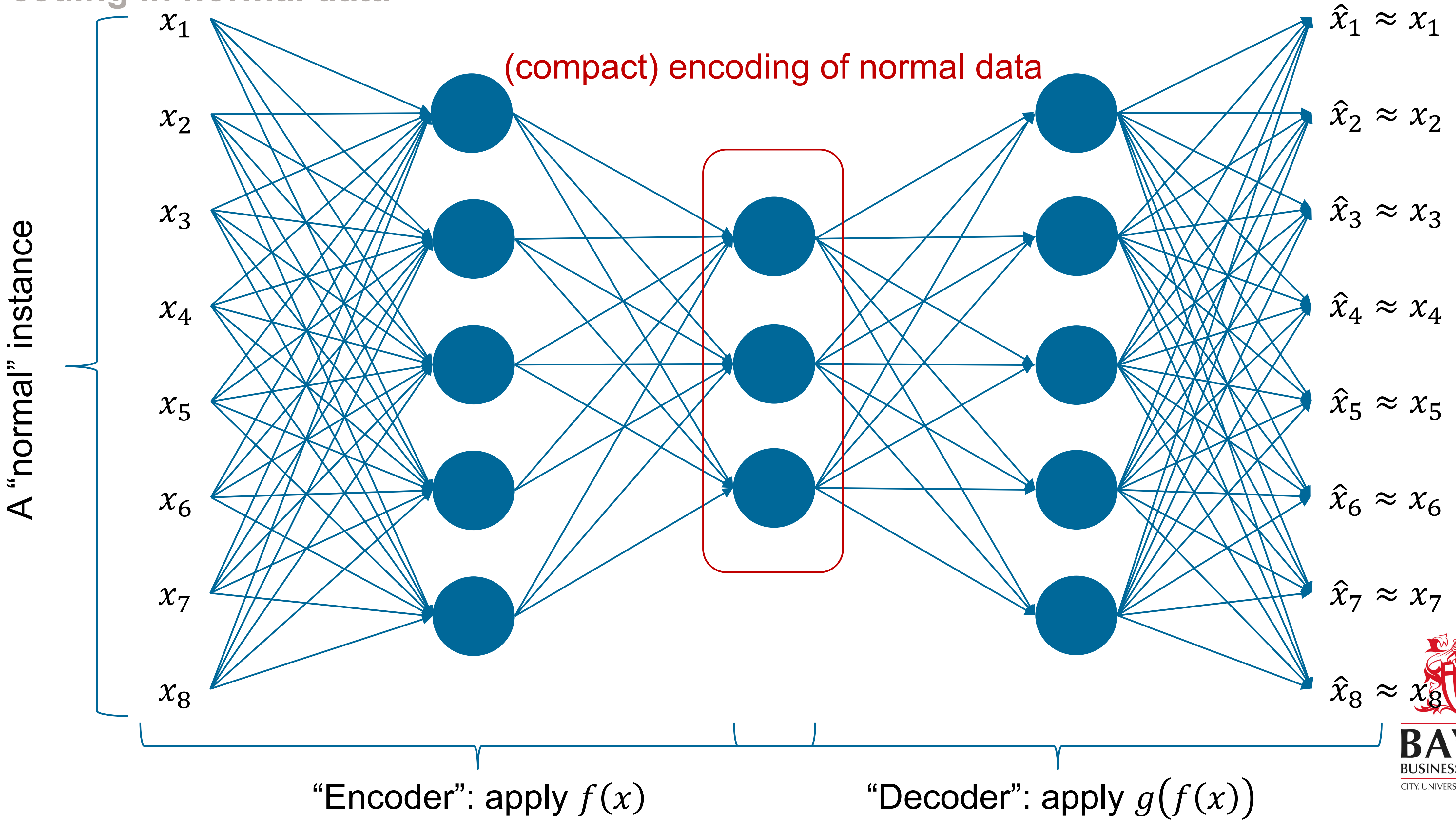
Feeding in normal data



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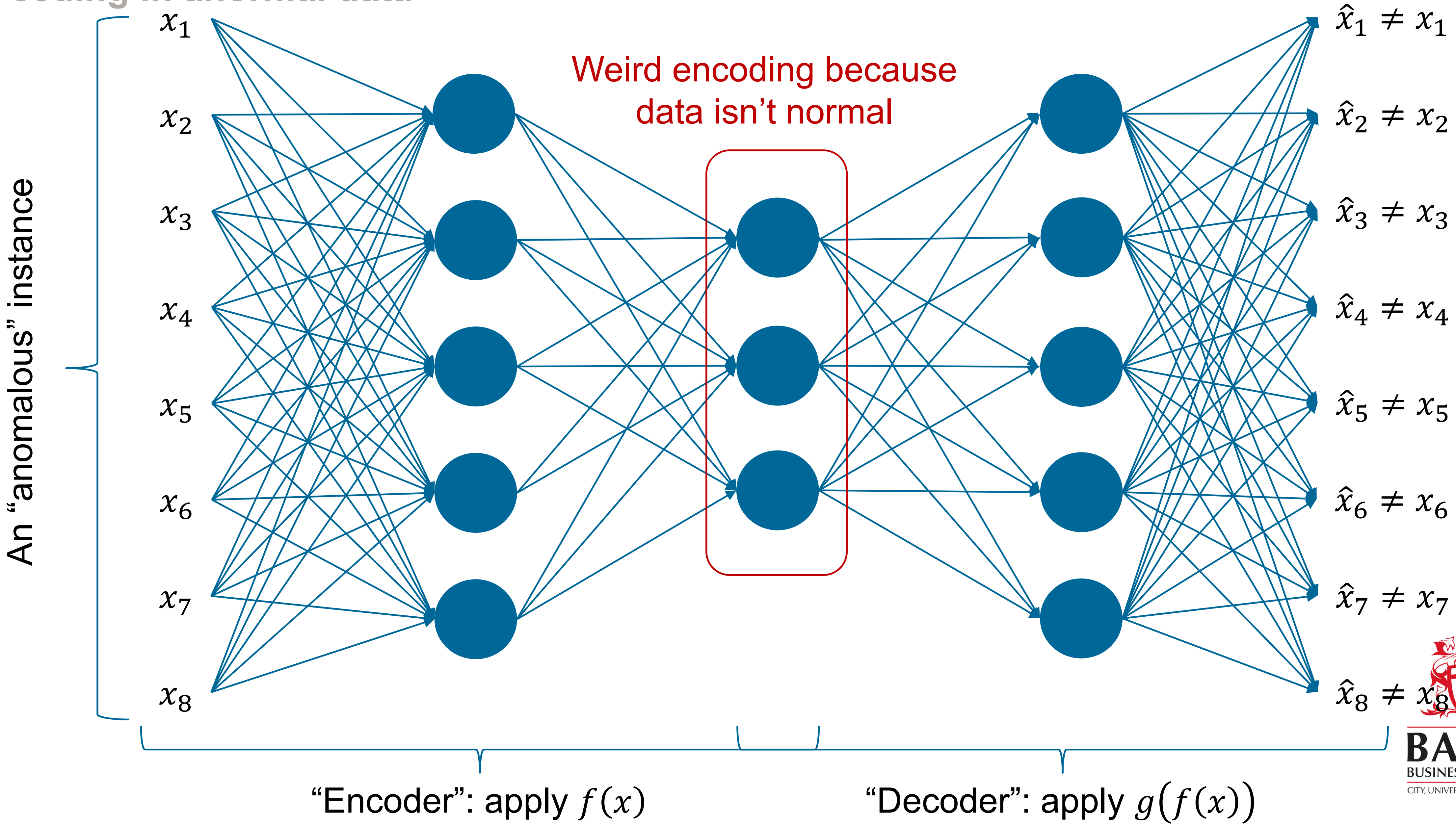
Feeding in anormal data



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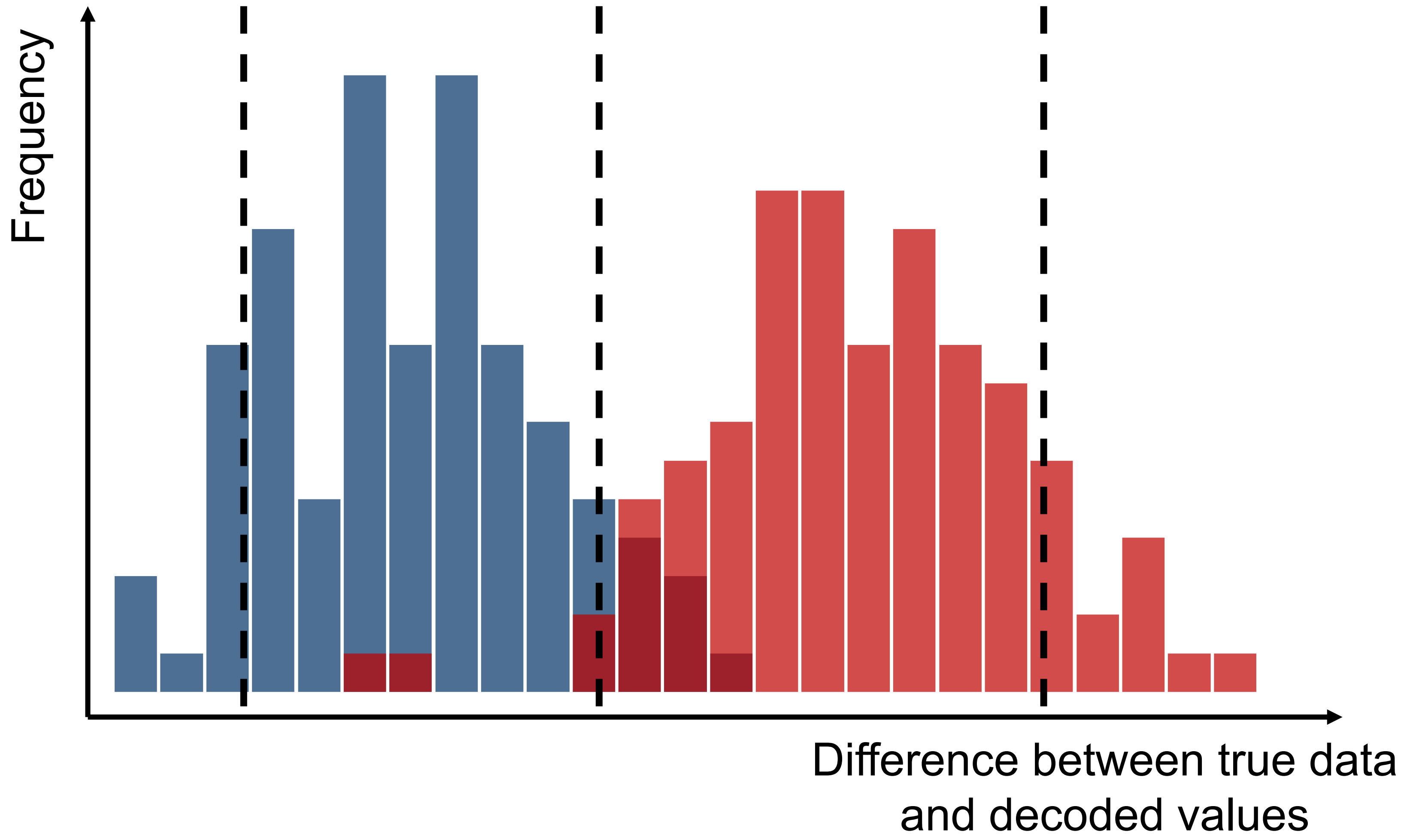
What should we be observing?



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Good luck with the assignment!