

The background of the slide features a complex, abstract pattern of blue and white wavy lines, resembling a fluid or a high-speed data flow, set against a solid black background. The lines are dense and create a sense of depth and movement.

Machine Learning in Physics: **Introduction**

Sadegh Raeisi

Outline

Why ML?

ML in Physics

Types of ML

Why ML?

It's best to review some examples.

ML in Science: Protein Folding

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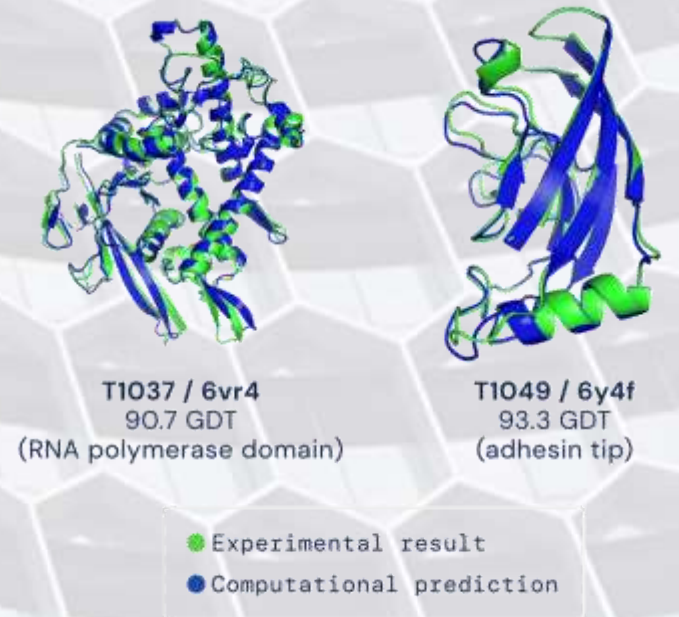
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Highly accurate protein structure prediction with AlphaFold

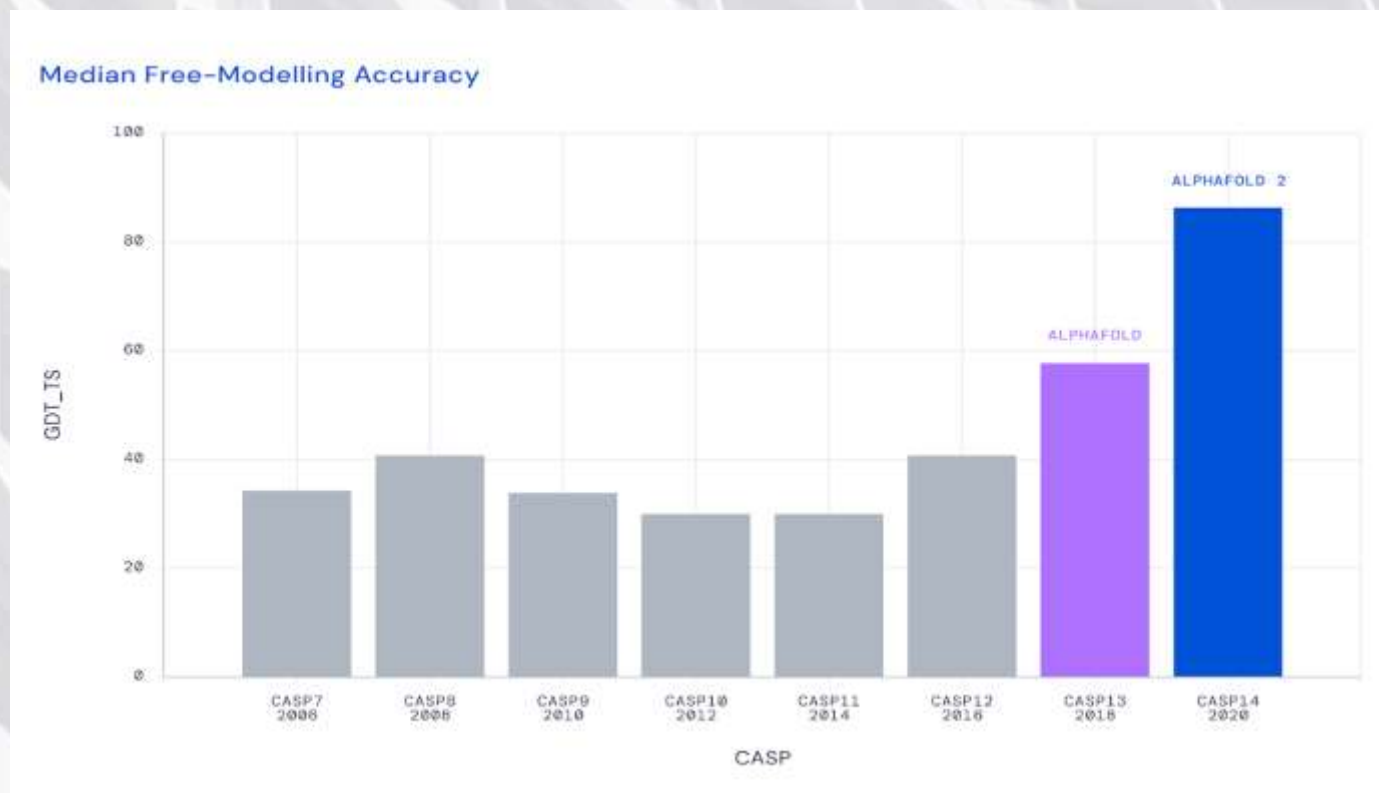
[John Jumper](#) , [Richard Evans](#), [...] [Demis Hassabis](#) 

Nature **596**, 583–589 (2021) | [Cite this article](#)

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ML in Science: Protein Folding



ML in Science: Drug discovery

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<p>Article Open Access Published: 12 July 2021</p> <h2>Artificial intelligence, protective therapy in</h2> <p>Debashis Sahoo ✉, Lee Swanson, Ibrahim M. Rama F. Pranadinata, Courtney Tindle, Mac Sandborn, Soumita Das ✉ & Pradipta Ghosh</p> <p><i>Nature Communications</i> 12, Article number 5285 Accesses 157 Altmetric Metrics</p>	<p>Review Article Published: 03 January 2020</p> <h2>Harnessing big ‘omics’ data and in hepatocellular carcinoma</h2> <p>Bin Chen ✉, Lana Garmire, Diego F. Calvisi, Mei-Sze Chua, Rolando</p> <p><i>Nature Reviews Gastroenterology & Hepatology</i> 17, 238–251 Accesses 24 Citations 48 Altmetric Metrics</p>	<p>Article Published: 15 April 2021</p> <h2>Optimization of therapeutic antibodies by predicting antigen specificity from antibody sequence via deep learning</h2> <p>Derek M. Mason, Simon Friedensohn, Cédric R. Weber, Christian Jordi, Bastian Wagner, Simon M. Meng, Roy A. Ehling, Lucia Bonati, Jan Dahinden, Pablo Gainza, Bruno E. Correia & Sai T. Reddy ✉</p> <p><i>Nature Biomedical Engineering</i> 5, 600–612 (2021) Cite this article</p> <p>4788 Accesses 2 Citations 145 Altmetric Metrics</p>

ML in Science: Mathematics

NewScientist

Volume 242, Issue 3228, 4 May 2019, Page 9

News & Technology

Machine learning

Google's AI mathematician

Leah Crane

HOList: An Environment for Machine Learning of Higher-Order Theorem Proving

Kshitij Bansal, Sarah M. Loos, Markus N. Rabe, Christian Szegedy, Stewart Wilcox

We present an environment, benchmark, and deep learning driven automated theorem prover for higher-order logic. Higher-order interactive theorem provers enable the formalization of arbitrary mathematical theories and thereby present an interesting, open-ended challenge for deep learning. We provide an open-source framework based on the HOL Light theorem prover that can be used as a reinforcement learning environment. HOL Light comes with a broad coverage of basic mathematical theorems on calculus and the formal proof of the Kepler conjecture, from which we derive a challenging benchmark for automated reasoning. We also present a deep reinforcement learning driven automated theorem prover, DeepHOL, with strong initial results on this benchmark.

Comments: Accepted at ICML 2019

Subjects: **Logic in Computer Science (cs.LO)**; Artificial Intelligence (cs.AI); Machine Learning (cs.LG)

Cite as: arXiv:1904.03241 [cs.LO]

(or arXiv:1904.03241v3 [cs.LO] for this version)

[\[1904.03241\] HOList: An Environment for Machine Learning of Higher-Order Theorem Proving \(arxiv.org\)](https://arxiv.org/abs/1904.03241)

Artificial intelligence trained by google learns to prove 1200 theorems.

ML in Science: writing books

Lithium-Ion Batteries

A Machine-Generated Summary of
Current Research

 Springer



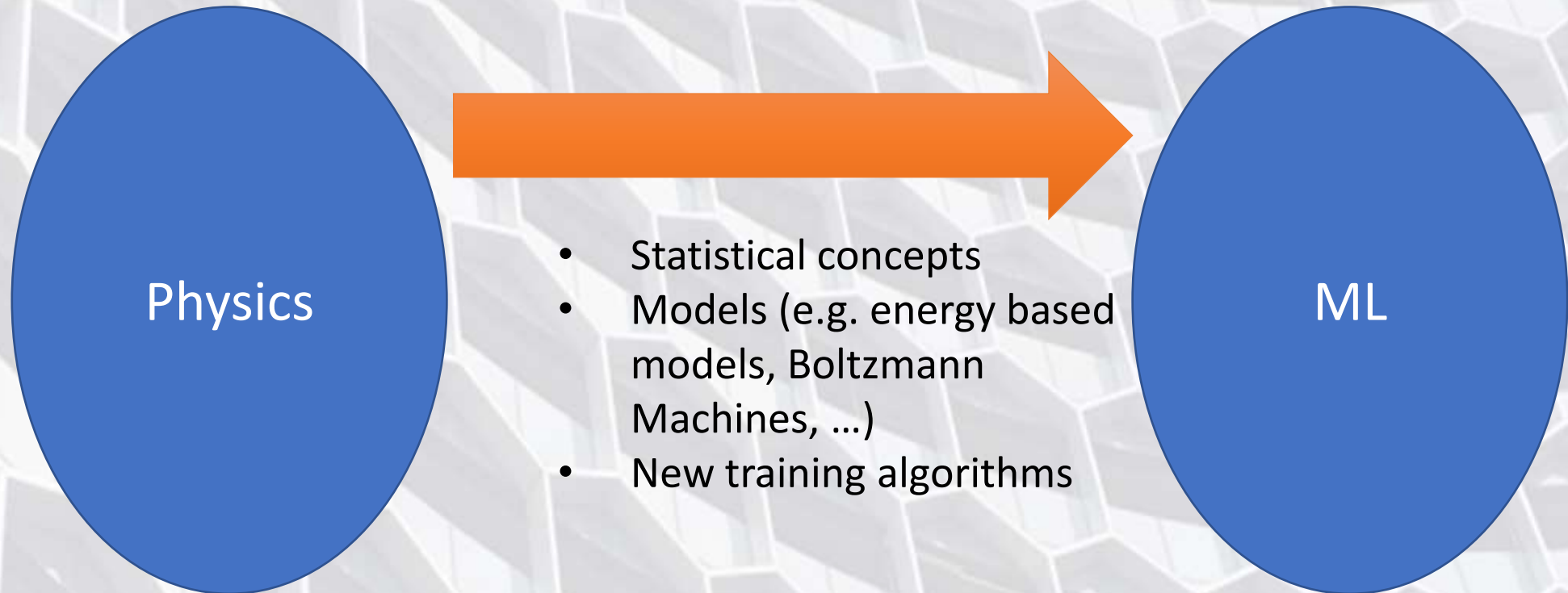
Can machines replace scientists?

What are the key aspects that cannot be replaced?

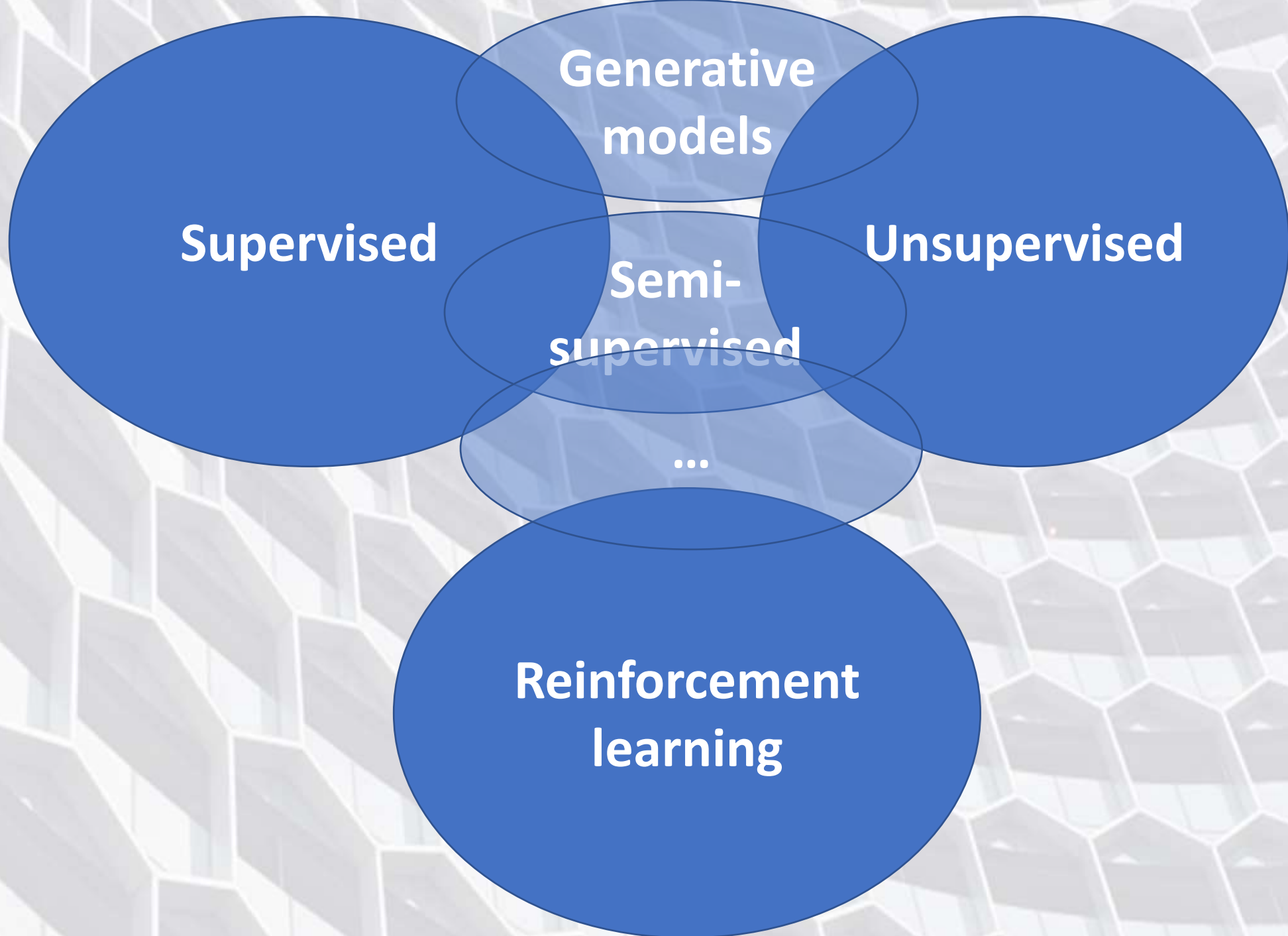
ML in Physics



ML in Physics



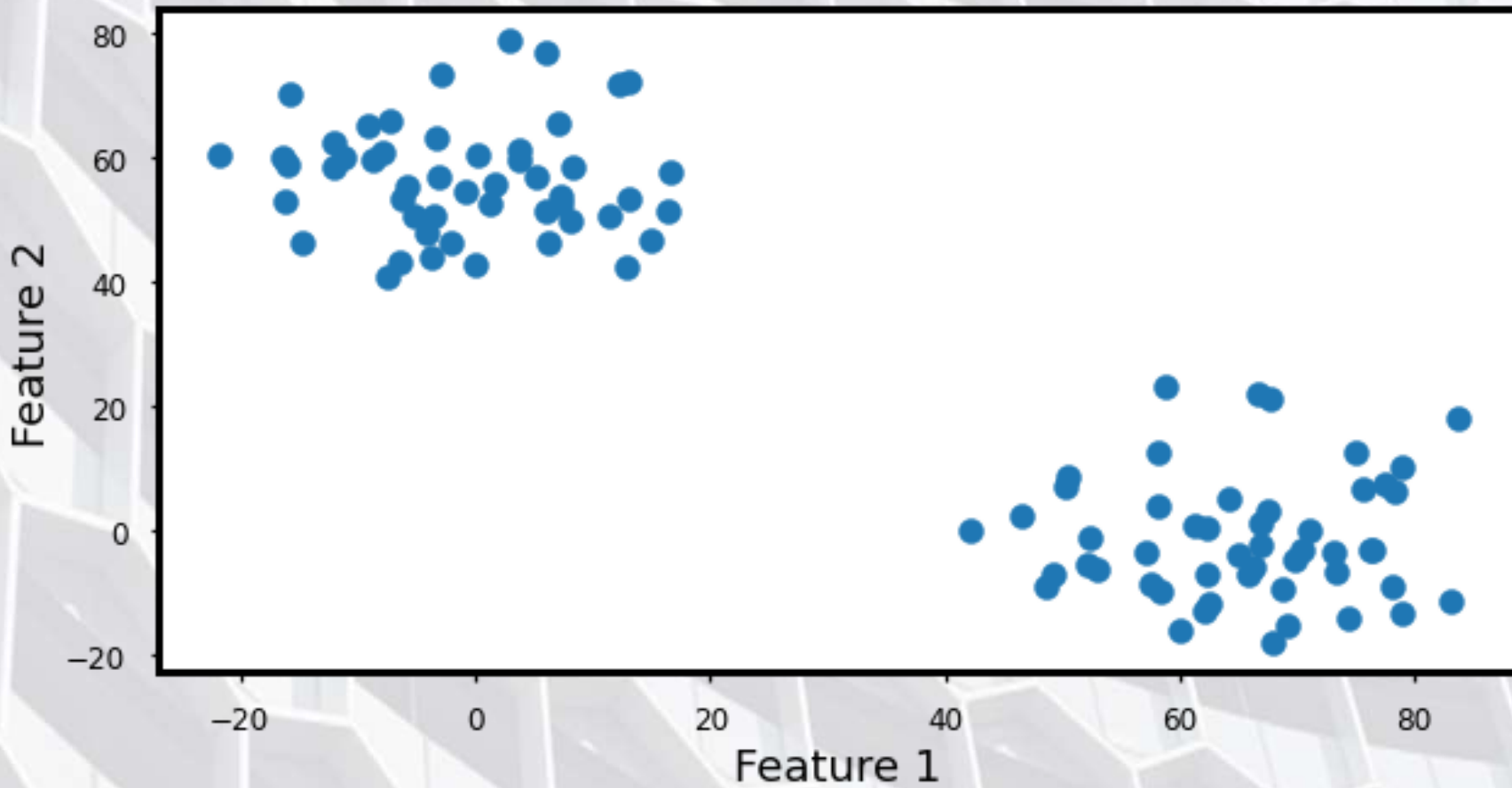
Types of ML



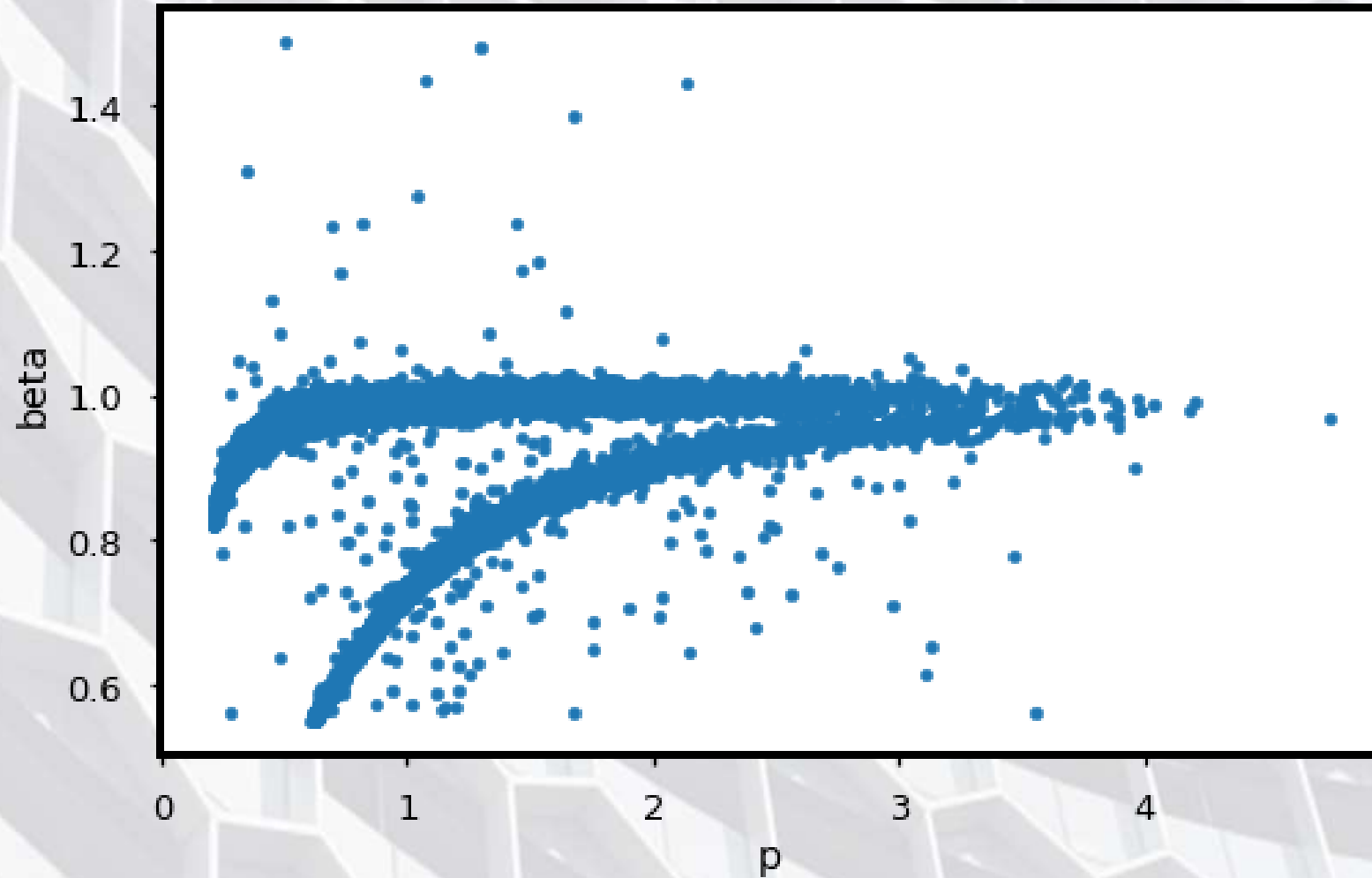
Unsupervised

- Clustering
- Dimensionality reduction
- Anomaly detection
- ...

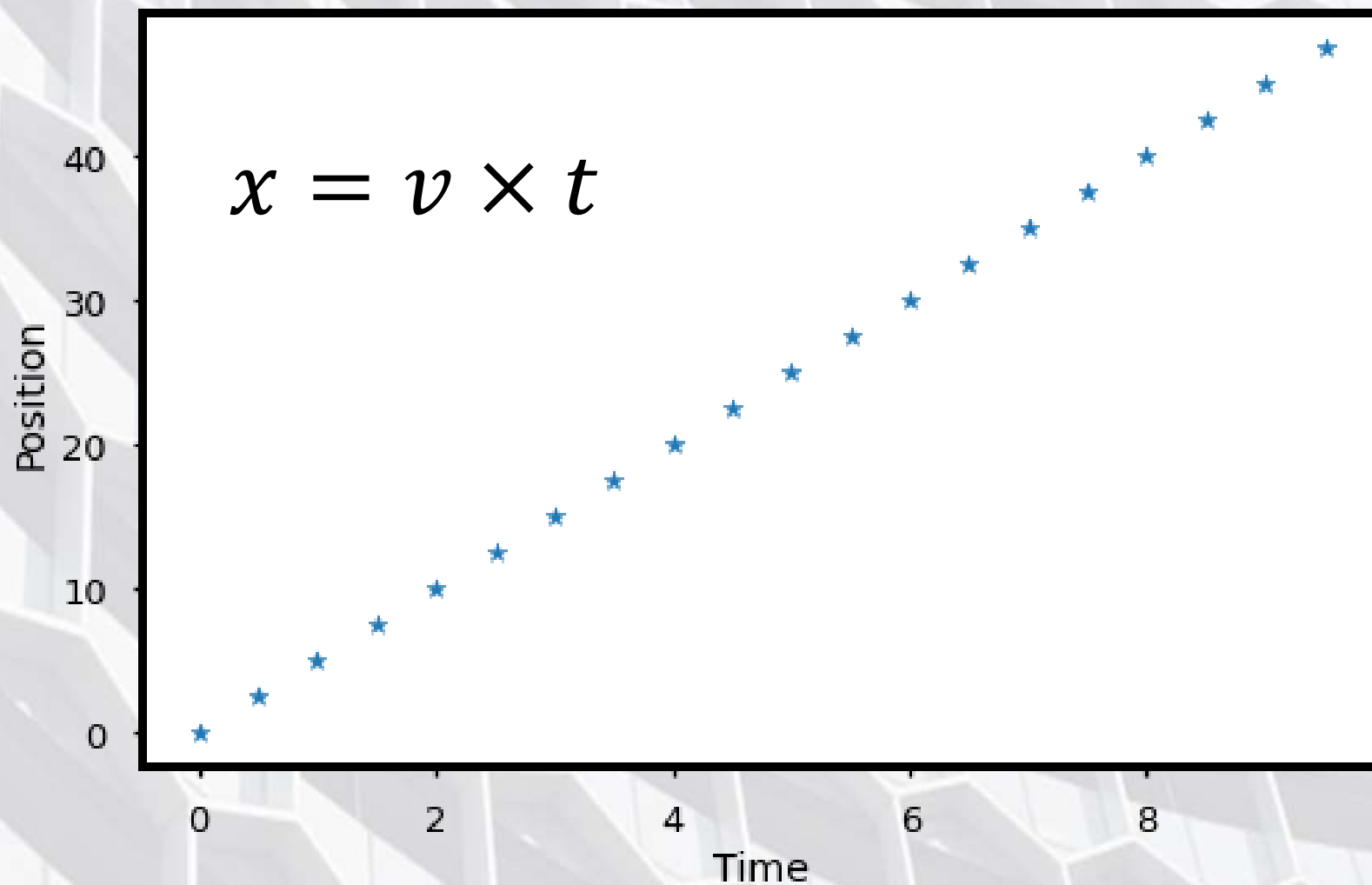
Unsupervised: Clustering



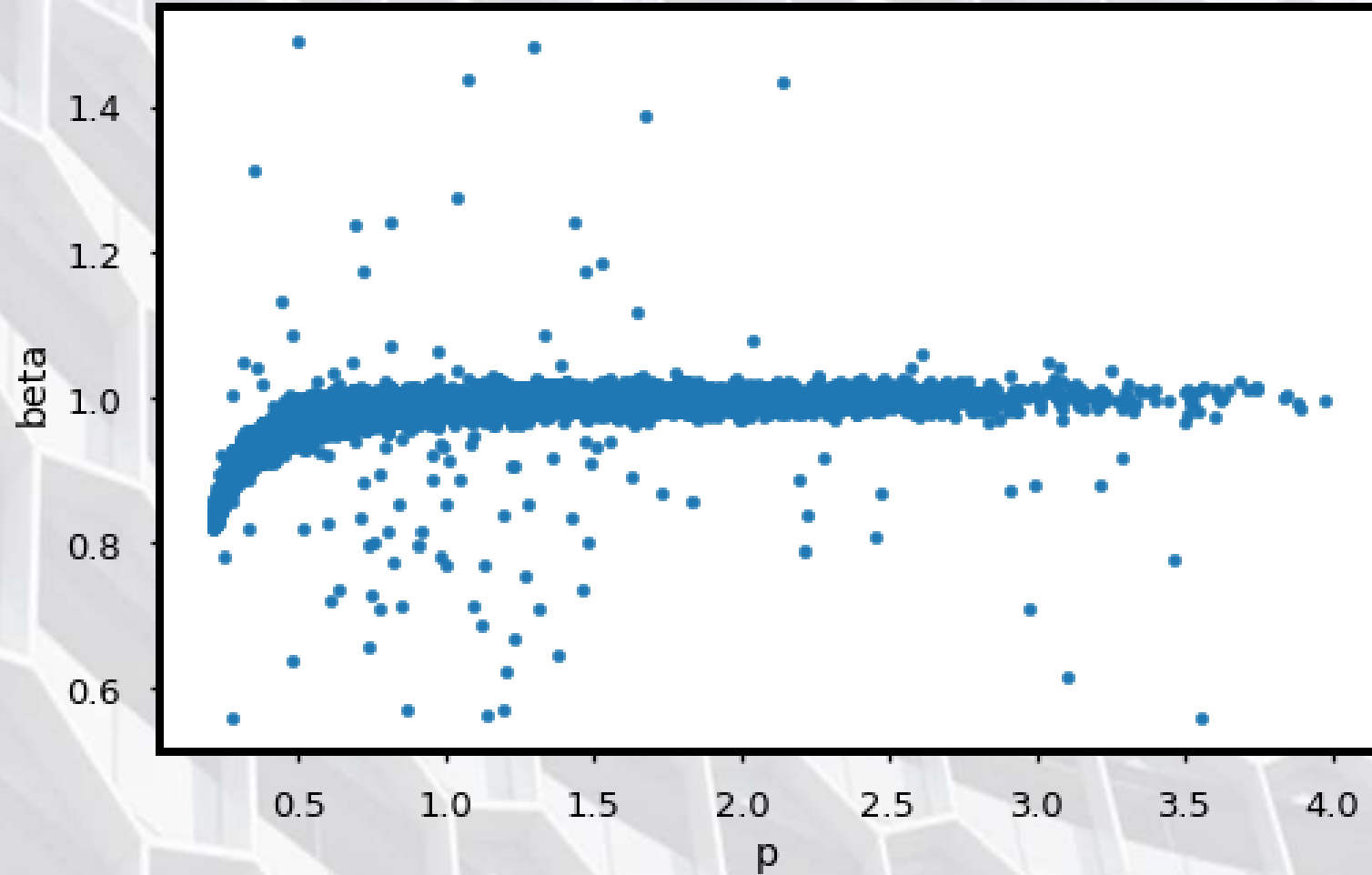
Unsupervised: Clustering



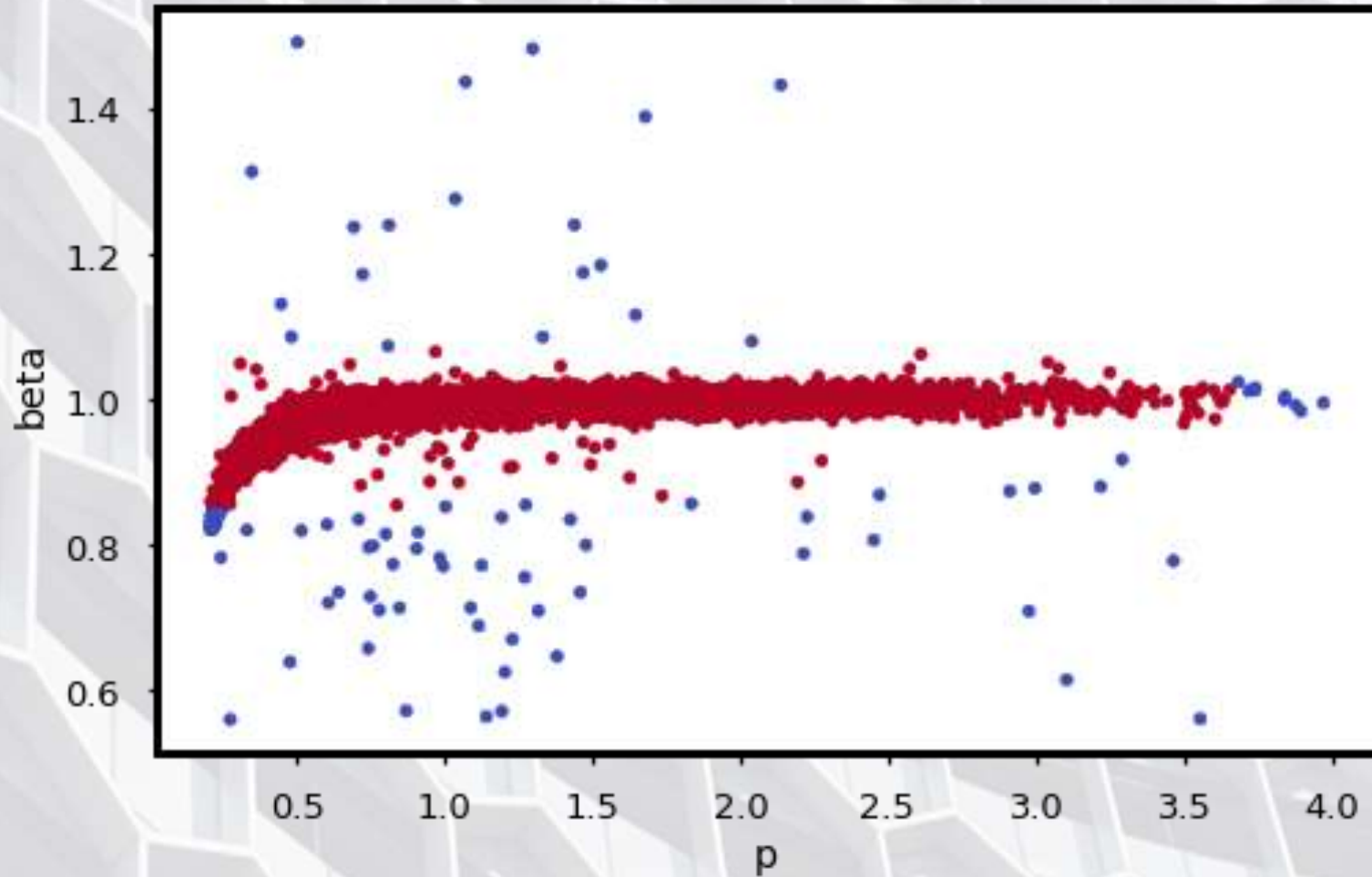
Unsupervised: Dimensionality reduction



Unsupervised: Anomaly detection



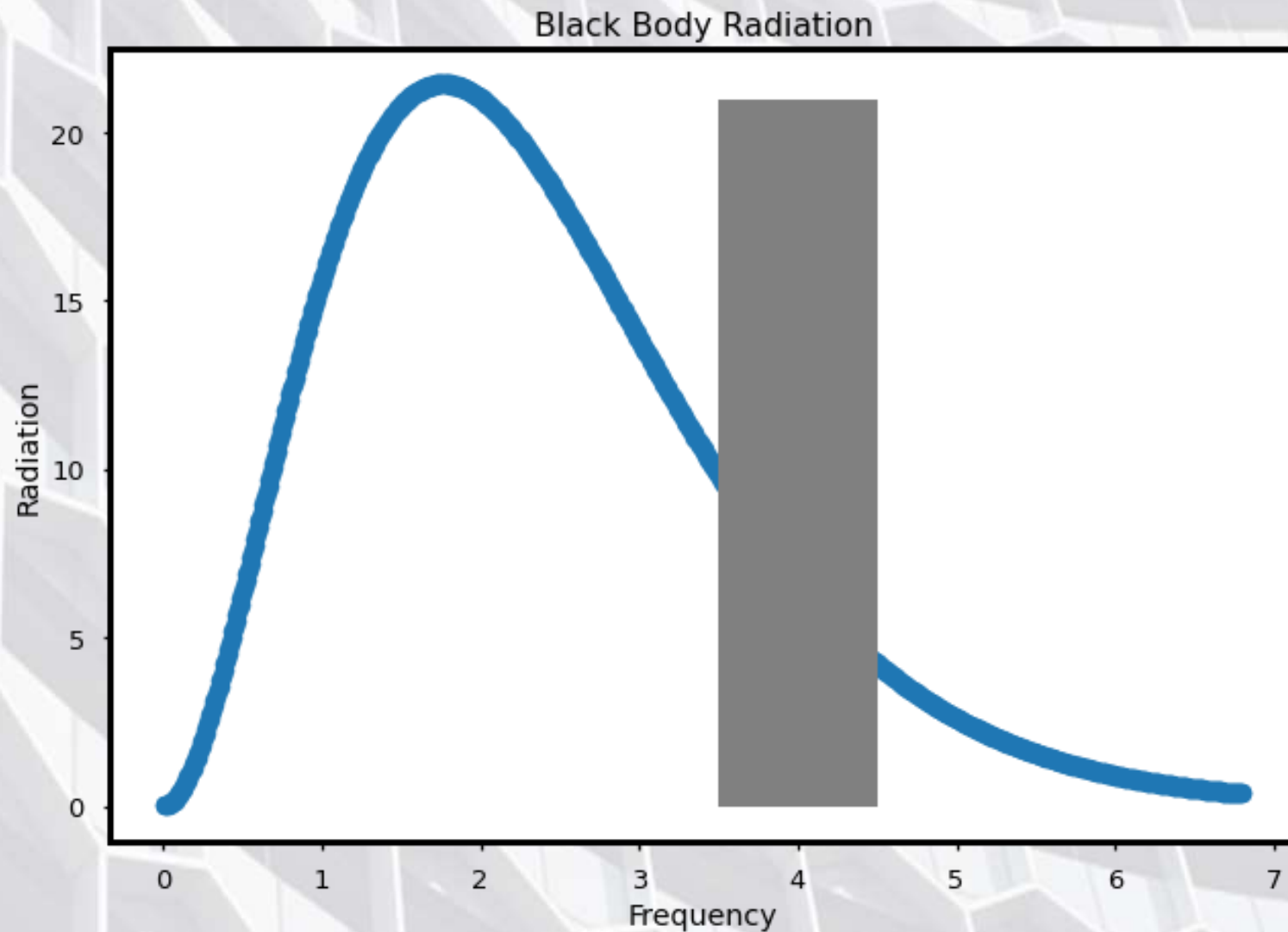
Unsupervised: Anomaly detection



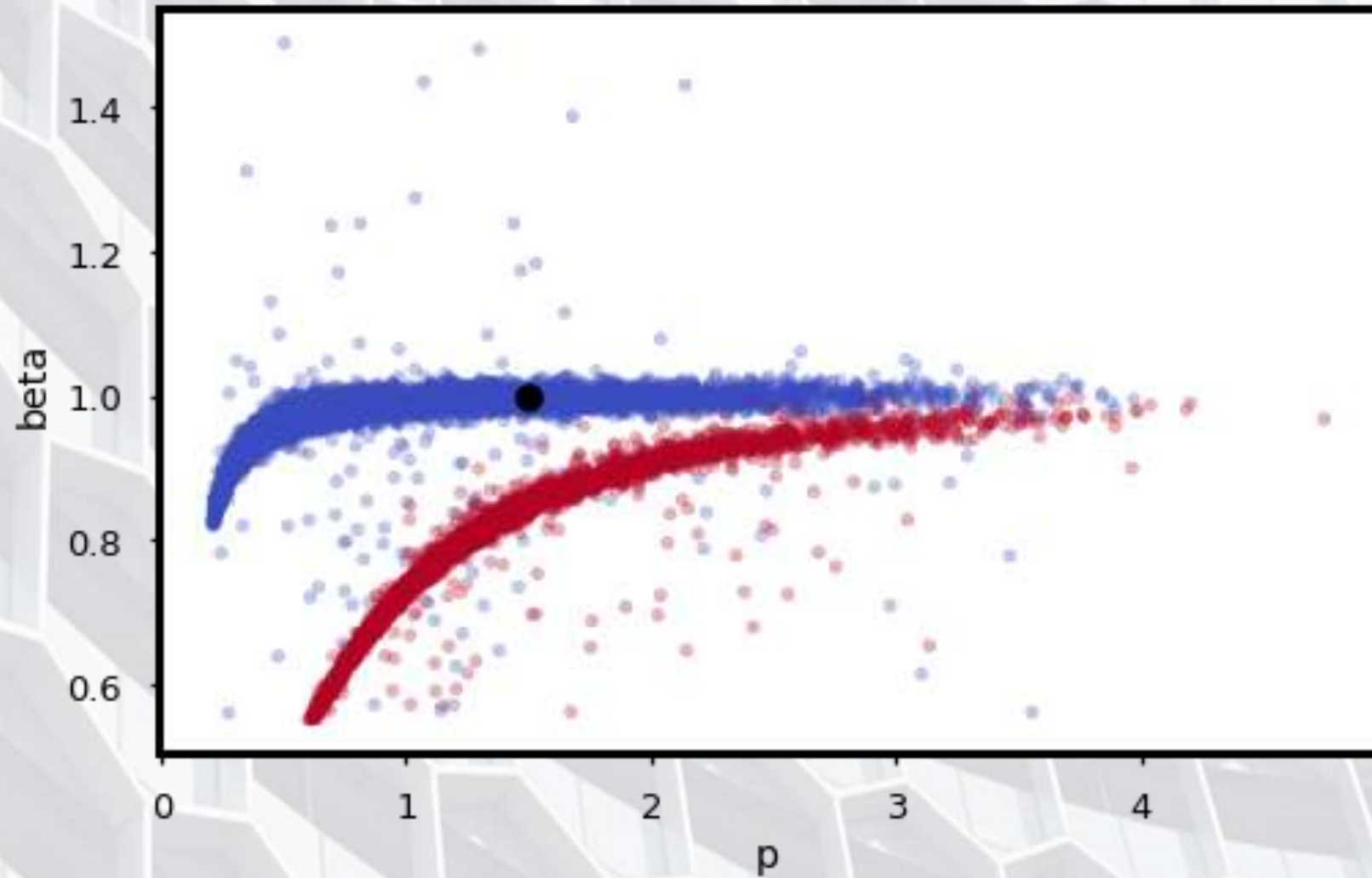
Supervised

- Regression
- Classification
- (Logistic Regression)

Supervised: Regression



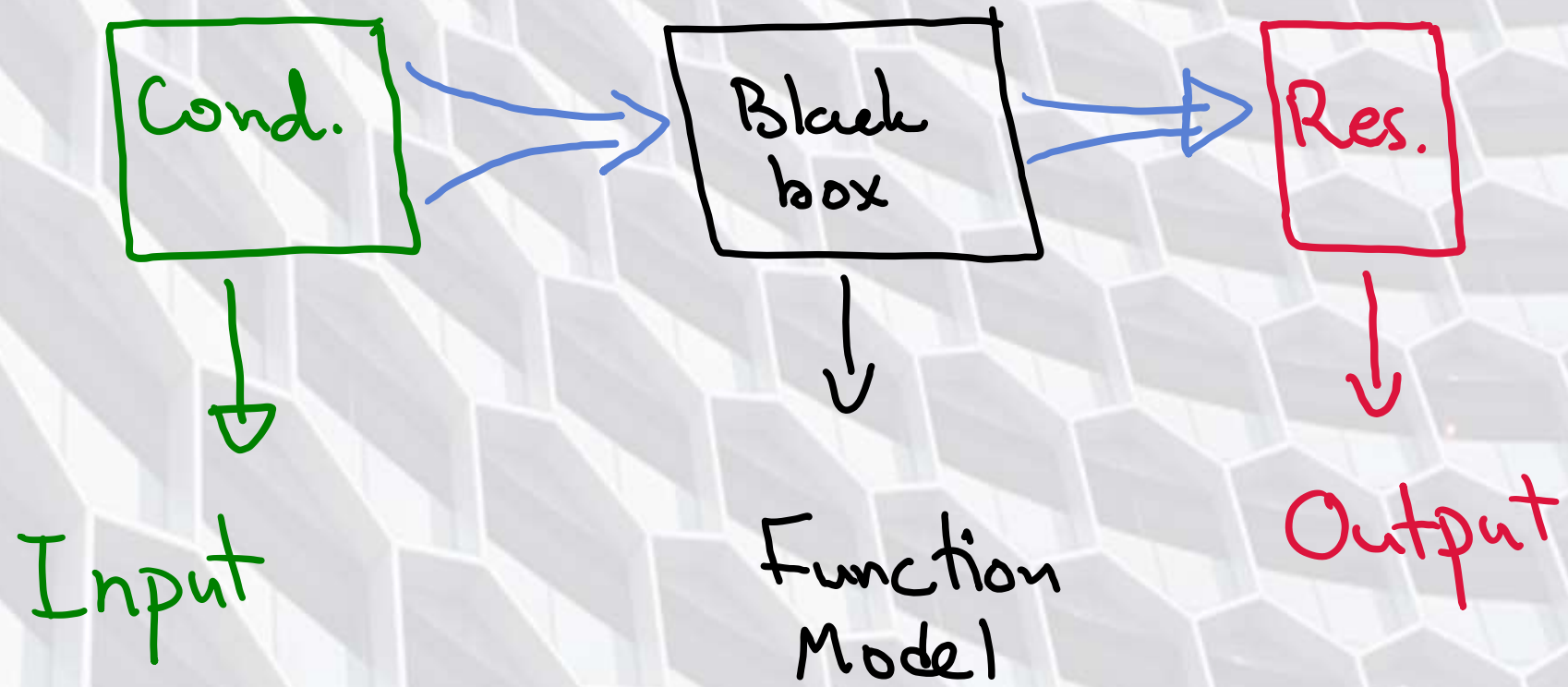
Supervised: Classification



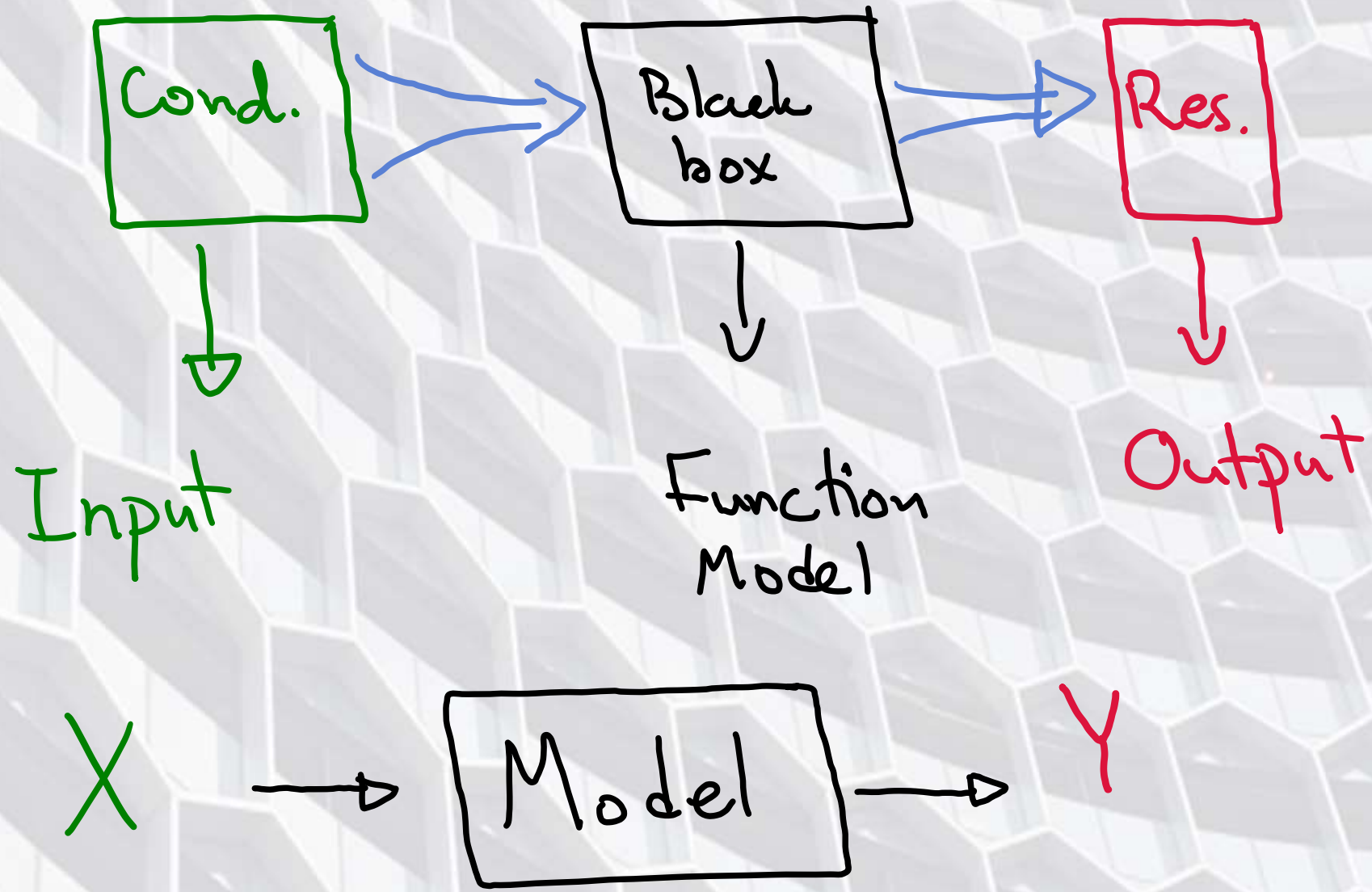
When do we use ML (supervised)

- We don't know how something works:
 - Complex systems with too many variables: weather ...
 - Complex systems with complex functionality
 - Simple problems that needs to be automated (boring ones)

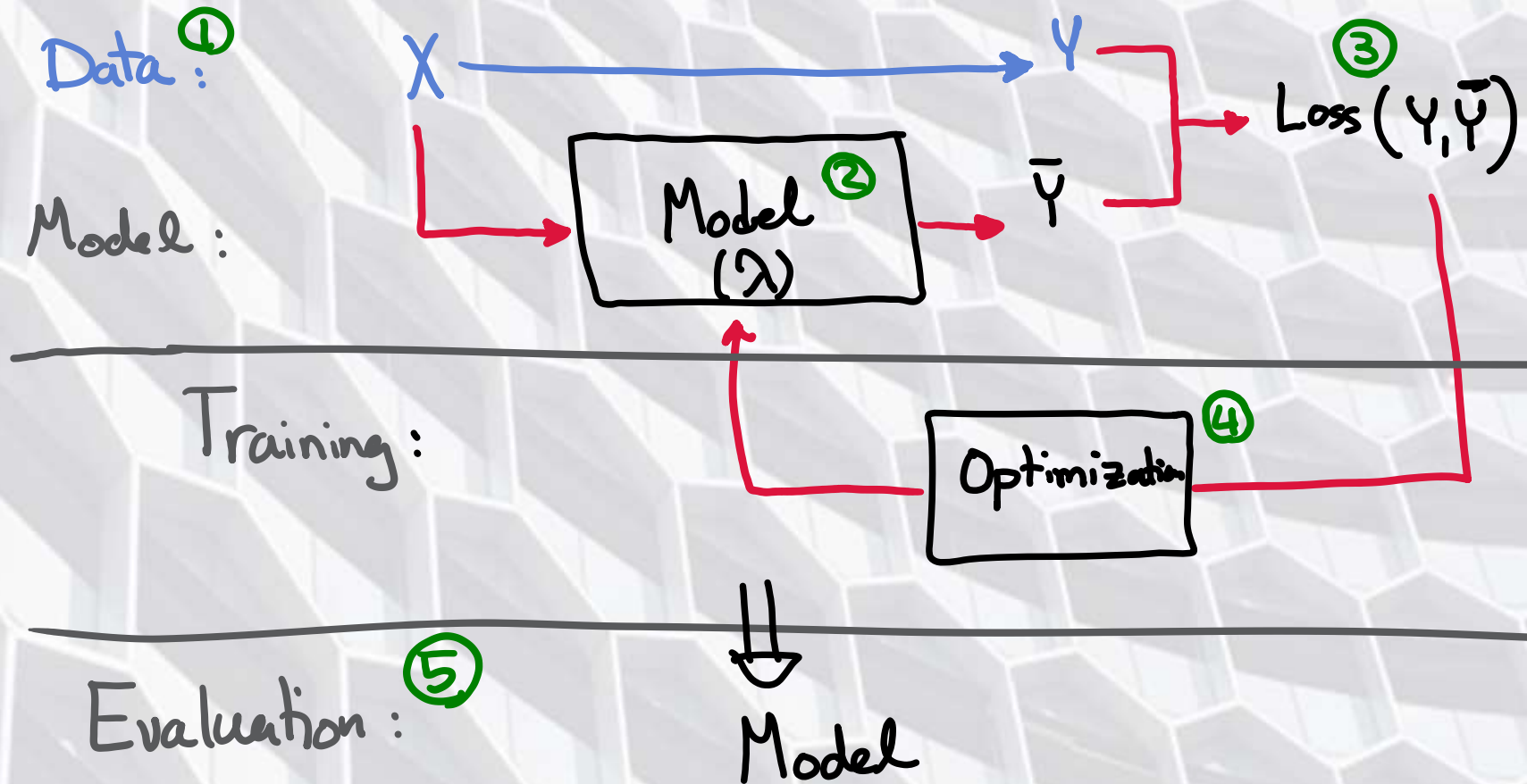
Supervised



Supervised



Supervised: Ingredients



Supervised: Ingredients

Hypothesis (Model)

Data

Distance function (loss)

Training algorithm

Evaluation metrics

Make a model

- Make a clustering algorithm
- Make a regression algorithm
- Make a classification algorithm