## PSY9511: Seminar 1

Introduction to machine learning

Esten H. Leonardsen 07.11.24



#### Outline

#### Plan for the day

- · Round of introductions
- · Course information
- · Introduction to machine learning
- Presentation of assignment 1



#### **Teacher**

#### Esten Høyland Leonardsen

- · Master's degree in Informatics: Programming and Networks
- · PhD in Psychology, deep learning applied to neuroimaging data
- Experience as a data scientist and programmer from the industry and various start-ups
- Post-doc at the center for Cognitive psychology, Neuroscience and Neuropsychology
- · Chief Scientific Officer at baba.vision
- Interests: Deep learning, explainable artificial intelligence, mental health, neuroimaging



#### **Students**

#### What I want to know about you

- · What's your name?
- · What department/section are you from?
- · What's your research project about?
- Do you have experience with machine learning and/or programming?
- What do you hope to learn from this course? (e.g. specific applications in your research, a theoretical understanding of machine learning, following and contributing to the public discourse, a future job in data science, ...)



#### Canvas

- All relevant announcements will be made on Canvas (e.g. changes to assignments, lectures, interesting reading material etc.)
- Lecture slides and notebooks from live coding will be put on Canvas before/after a lecture



#### Curriculum

- The course relies on the book "An Introduction to Statistical Learning", available at https://www.statlearning.com/
  - Only some chapters will be used, they are posted on Canvas under each Lecture module
  - Although we won't be relying much on the exercises i highly recommend looking into them yourselves
- I will add some scientific publications to the curriculum list as we go, depending on your preferences and interests



#### Exercises

- The course has no exam, but six mandatory exercises you will need to pass
  - · Mostly practical coding, with some reflection
  - Given with a hard deadline, unless there is a good reason for an extension
  - Can be delivered multiple times based on feedback (but the first must be in time for the original deadline)
- Exercises 1-4 and 6 are mostly small and related to specific content of the preceding lecture, while 5 is a bit larger
- You should hand in runnable code (e.g. a Jupyter notebook, a python script, an R script, Rmarkdown etc.), not code copied into a Word document or a pdf



#### Generative artificial intelligence (e.g. ChatGPT)

- You are allowed to use generative AI in the assignments, but you must state where and how
  - Be critical, you should be able to understand and explain all the code you hand in



#### Lectures

- Goal is to show you the underlying theory in an intuitive manner
- ~2 hours of lecturing, ~1 hour for individual work/help with assignments
  - · You will have to practice what you learn yourself
- Will try to make lectures interactive, and do live coding where possible



#### Course plan

- 1. Introduction to machine learning
- 2. Basics of regression and classification
- 3. Variable selection and regularization
- 4. Model selection, validation, and testing
- 5. Non linearity: Splines and tree-based methods
- 6. Unsupervised learning
- 7. Deep learning and image processing
- 8. Language processing



# Introduction to machine learning



#### Key terminology:

• Statistical learning: A set of tools (often called models) for understanding data



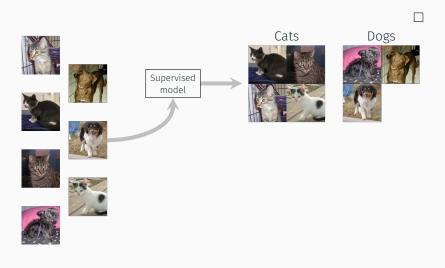
#### Key terminology:

- Statistical learning: A set of tools (often called models) for understanding data
- · Supervised learning: We know what task we want to solve
- Unsupervised learning: We don't know what task we want to solve (or we don't have the data we need to solve it)

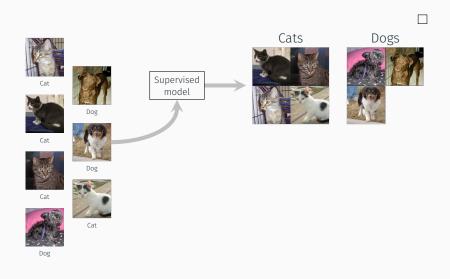




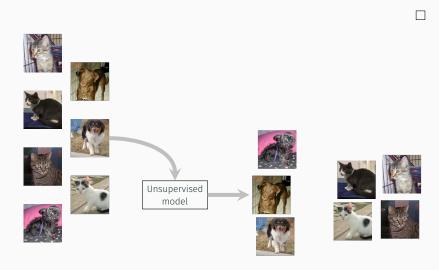




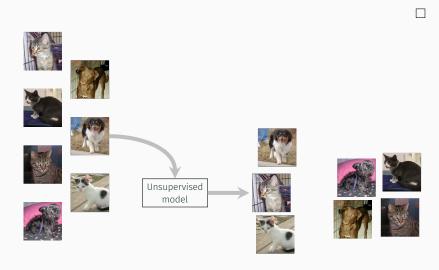














name	year	cylinders	horsepower	weight	mpg
Chevrolet Chevelle Malibu	1970	8	130	3504	18
Buick Skylark 320	1980	4	165	3693	15
Plymouth Satellite	1971	8	150	3436	18
AMC Rebel SST	1975	4	150	3433	16
Ford Torino	1978	8	140	3449	17

#### Prerequisites

· A dataset representing a given population



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#### Prerequisites

- · A dataset representing a given population
- · A response-variable y that we want to predict



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#### Prerequisites

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- A set of predictors X that we can use to predict y

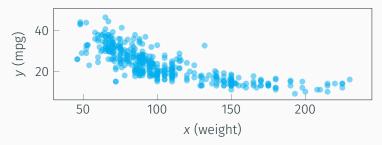


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#### Prerequisites

- · A dataset representing a given population
- A response-variable *y* that we want to predict
- A set of predictors X that we can use to predict y
- An **assumed** relationship between X and y that can be described by an unknown function f, such that  $y = f(X) + \epsilon$

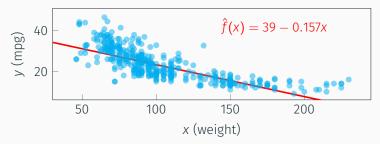




### Estimation (or training the model)

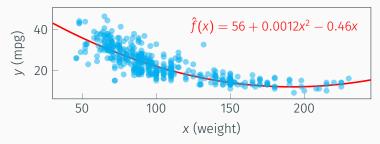
• We have assumed that  $y = f(X) + \epsilon$ , but don't know f





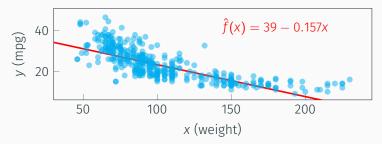
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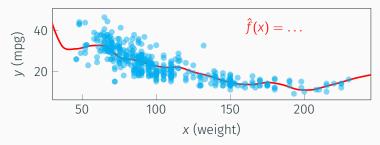




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- $\cdot$  Parametric models:  $\hat{f}$  has a simple form

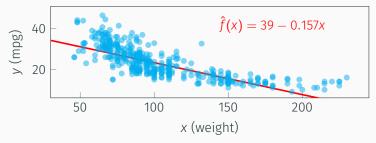
$$\cdot \hat{f}(x) = \beta_0 + \beta_1 x$$





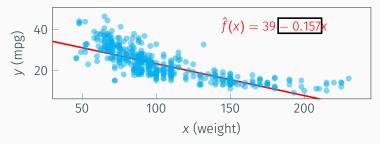
- We have assumed that  $y = f(X) + \epsilon$ , but don't know f
- · We produce an estimate  $\hat{f}$
- Parametric models:  $\hat{f}$  has a simple form
  - $\cdot \hat{f}(x) = \beta_0 + \beta_1 x$
- $\cdot$  Non-parametric models:  $\hat{f}$  relies directly on the data





Inference: Understanding the relationship between the predictors and the response

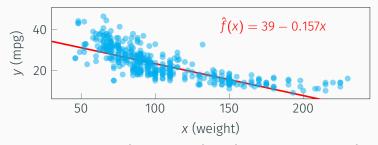




Inference: Understanding the relationship between the predictors and the response

How does individual features relate to the response?

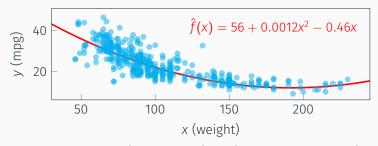




Inference: Understanding the relationship between the predictors and the response

- How does individual features relate to the response?
- · What is the functional form?



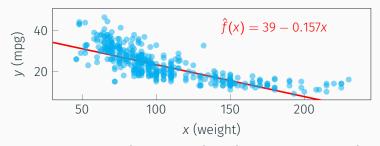


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Prediction: Predicting the response for new observations



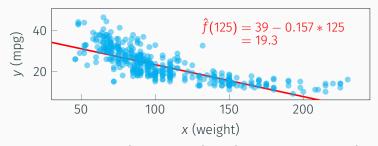


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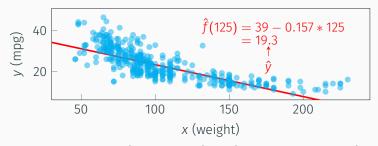


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