

IN5550: Neural Methods in Natural Language
Processing
Sub-lecture 2.1
Supervised Machine Learning

Andrey Kutuzov

University of Oslo

31 January 2023





1 Introduction

2 Basics of supervised machine learning



I am Andrey Kutuzov

I will do **some of the lectures**, covering the following topics:



I am Andrey Kutuzov

I will do **some of the lectures**, covering the following topics:

- ▶ a review of supervised learning (introducing notation)



I am Andrey Kutuzov

I will do **some of the lectures**, covering the following topics:

- ▶ a review of supervised learning (introducing notation)
- ▶ linear classifiers and simple feed-forward neural networks



I am Andrey Kutuzov

I will do **some of the lectures**, covering the following topics:

- ▶ a review of supervised learning (introducing notation)
- ▶ linear classifiers and simple feed-forward neural networks
- ▶ multi-layer neural networks and their training



I am Andrey Kutuzov

I will do **some of the lectures**, covering the following topics:

- ▶ a review of supervised learning (introducing notation)
- ▶ linear classifiers and simple feed-forward neural networks
- ▶ multi-layer neural networks and their training
- ▶ language modeling and distributed word embeddings
- ▶ recurrent neural networks (RNNs) and contextualized embeddings



I am Andrey Kutuzov

I will do **some of the lectures**, covering the following topics:

- ▶ a review of supervised learning (introducing notation)
- ▶ linear classifiers and simple feed-forward neural networks
- ▶ multi-layer neural networks and their training
- ▶ language modeling and distributed word embeddings
- ▶ recurrent neural networks (RNNs) and contextualized embeddings

I am also partially responsible for the **obligatory assignments**:

1. Bag of Words Document Classification
2. ...
3. ...



Technicalities

- ▶ Familiarize yourself with the **course infrastructure**.



Technicalities

- ▶ Familiarize yourself with the **course infrastructure**.
- ▶ Check the course page for messages.



Technicalities

- ▶ Familiarize yourself with the **course infrastructure**.
- ▶ Check the course page for messages.
- ▶ Test whether you can access `https://github.uio.no/in5550/2023`
 - ▶ make sure to update your UiO GitHub profile with your photo, and star the course repository :-)



Technicalities

- ▶ Familiarize yourself with the **course infrastructure**.
- ▶ Check the course page for messages.
- ▶ Test whether you can access `https://github.uio.no/in5550/2023`
 - ▶ make sure to update your UiO GitHub profile with your photo, and star the course repository :-)
- ▶ Most of machine learning revolves around **linear algebra**.



Technicalities

- ▶ Familiarize yourself with the **course infrastructure**.
- ▶ Check the course page for messages.
- ▶ Test whether you can access `https://github.uio.no/in5550/2023`
 - ▶ make sure to update your UiO GitHub profile with your photo, and star the course repository :-)
- ▶ Most of machine learning revolves around **linear algebra**.
- ▶ We created a *LinAlg* cheat sheet for this course.



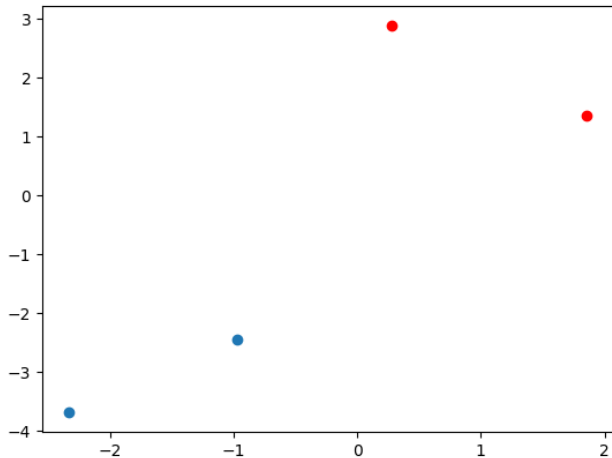
Technicalities

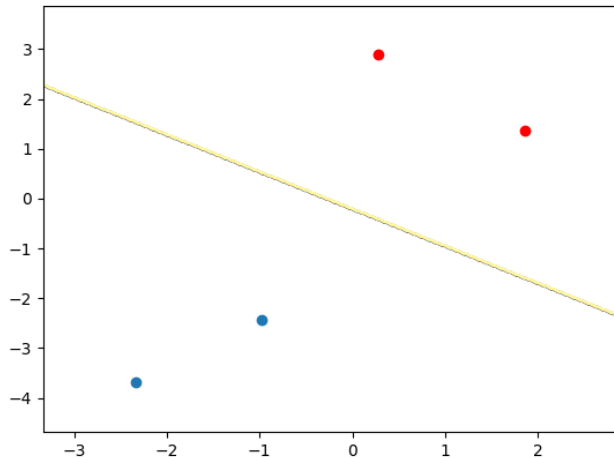
- ▶ Familiarize yourself with the **course infrastructure**.
- ▶ Check the course page for messages.
- ▶ Test whether you can access `https://github.uio.no/in5550/2023`
 - ▶ make sure to update your UiO GitHub profile with your photo, and star the course repository :-)
- ▶ Most of machine learning revolves around **linear algebra**.
- ▶ We created a *LinAlg* cheat sheet for this course.
 - ▶ Linked from the course page, adapted for the notation of [Goldberg, 2017].

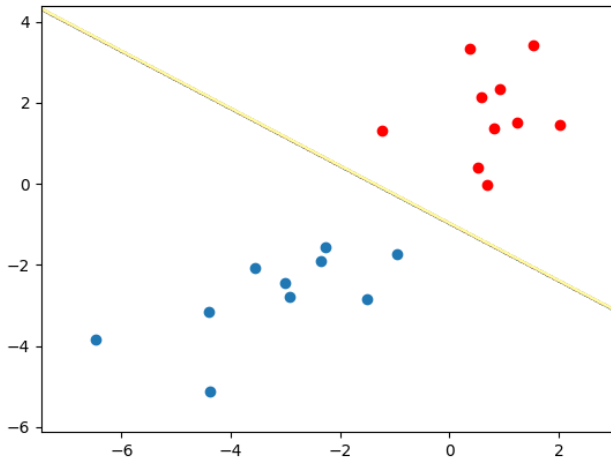


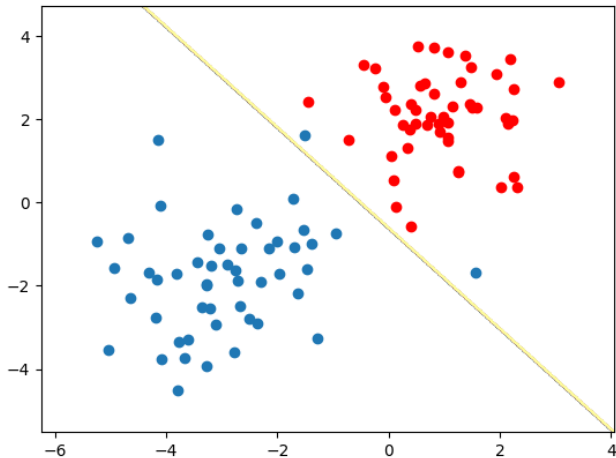
1 Introduction

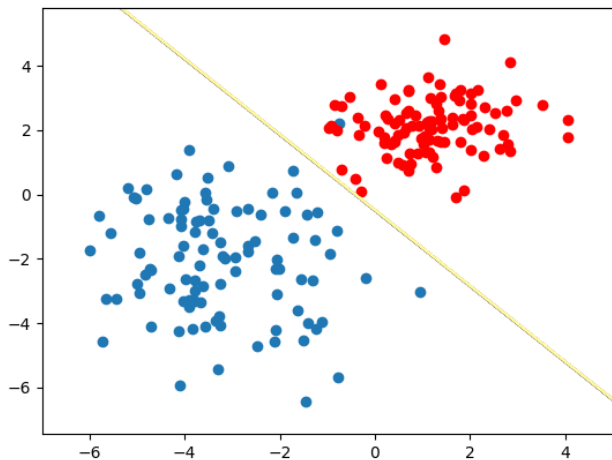
2 Basics of supervised machine learning

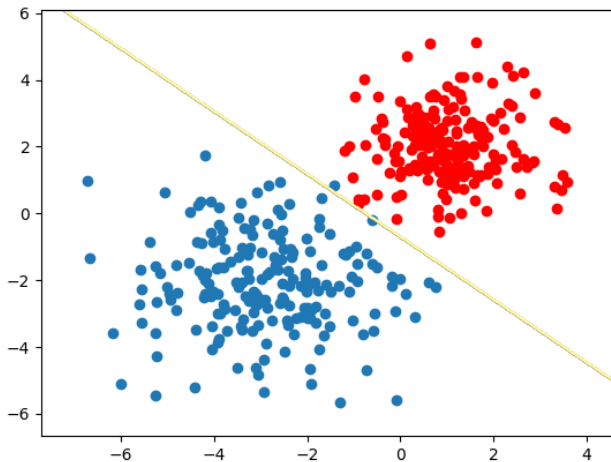


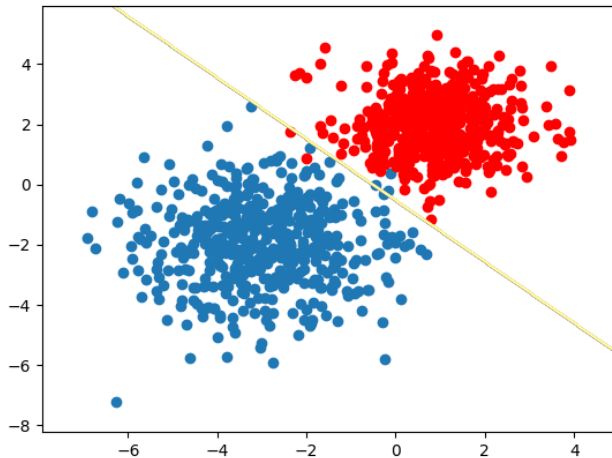














- ▶ Input 1: a training set of n training instances $x_{1:n} = x_1, x_2, \dots, x_n$



- ▶ Input 1: a training set of n training instances $x_{1:n} = x_1, x_2, \dots, x_n$
 - ▶ for example, e-mail messages.



- ▶ Input 1: a training set of n training instances $x_{1:n} = x_1, x_2, \dots, x_n$
 - ▶ for example, e-mail messages.
- ▶ Input 2: corresponding 'gold' labels for these instances
 $y_{1:n} = y_1, y_2, \dots, y_n$



- ▶ Input 1: a training set of n training instances $x_{1:n} = x_1, x_2, \dots, x_n$
 - ▶ for example, e-mail messages.
- ▶ Input 2: corresponding 'gold' labels for these instances
 $y_{1:n} = y_1, y_2, \dots, y_n$
 - ▶ for example, whether the message is spam (1) or not (0).



- ▶ Input 1: a training set of n training instances $x_{1:n} = x_1, x_2, \dots, x_n$
 - ▶ for example, e-mail messages.
- ▶ Input 2: corresponding 'gold' labels for these instances
 $y_{1:n} = y_1, y_2, \dots, y_n$
 - ▶ for example, whether the message is spam (1) or not (0).
- ▶ The trained models allow to **make label predictions for unseen instances.**



- ▶ Input 1: a training set of n training instances $x_{1:n} = x_1, x_2, \dots, x_n$
 - ▶ for example, e-mail messages.
- ▶ Input 2: corresponding 'gold' labels for these instances
 $y_{1:n} = y_1, y_2, \dots, y_n$
 - ▶ for example, whether the message is spam (1) or not (0).
- ▶ The trained models allow to **make label predictions for unseen instances.**
- ▶ Generally: **some program for mapping instances to labels.**



Recap on data split

- ▶ Recall: we want the model to make good predictions for **unseen** data.

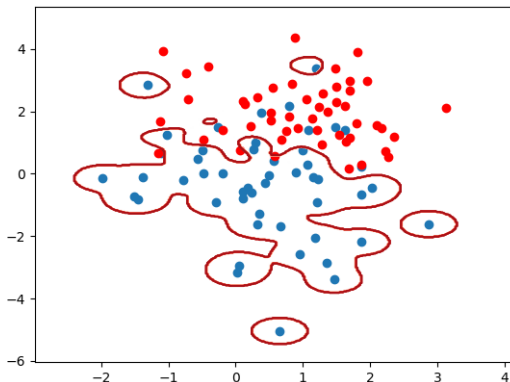


Recap on data split

- ▶ Recall: we want the model to make good predictions for **unseen** data.
- ▶ It should not **overfit** to the seen data.

Recap on data split

- ▶ Recall: we want the model to make good predictions for **unseen** data.
- ▶ It should not **overfit** to the seen data.





Remember: we want models that **generalize**

- ▶ Thus, the datasets are usually split into:
 1. **train data**;



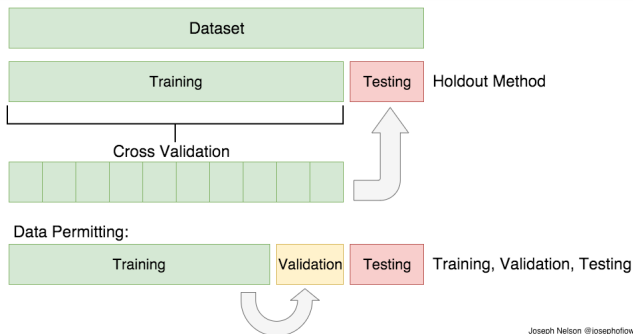
Remember: we want models that **generalize**

- ▶ Thus, the datasets are usually split into:
 1. **train data**;
 2. **validation/development data** (optional);

Remember: we want models that **generalize**

► Thus, the datasets are usually split into:

1. **train data**;
2. **validation/development data** (optional);
3. **test/held-out data**.





- ▶ We want to find a function which makes good, generalizable predictions for our task.



- ▶ We want to find a function which makes good, generalizable predictions for our task.
- ▶ Searching among **all** possible functions is unfeasible.



- ▶ We want to find a function which makes good, generalizable predictions for our task.
- ▶ Searching among **all** possible functions is unfeasible.
- ▶ To cope with that, we choose an **inductive bias**...



- ▶ We want to find a function which makes good, generalizable predictions for our task.
- ▶ Searching among **all** possible functions is unfeasible.
- ▶ To cope with that, we choose an **inductive bias**...
- ▶ ...and set some **hypothesis class**...

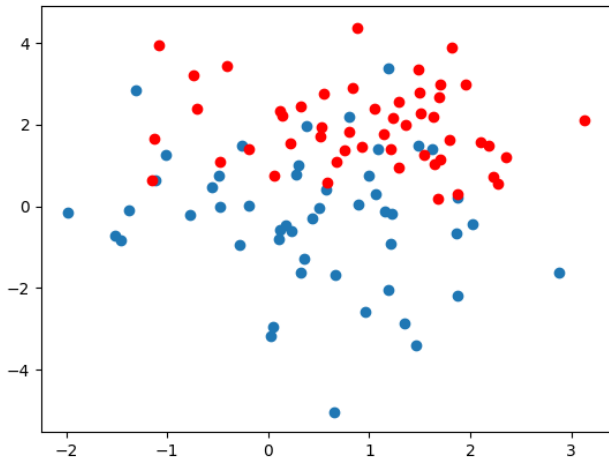


- ▶ We want to find a function which makes good, generalizable predictions for our task.
- ▶ Searching among **all** possible functions is unfeasible.
- ▶ To cope with that, we choose an **inductive bias**...
- ▶ ...and set some **hypothesis class**...
- ▶ ...to search only within this class.

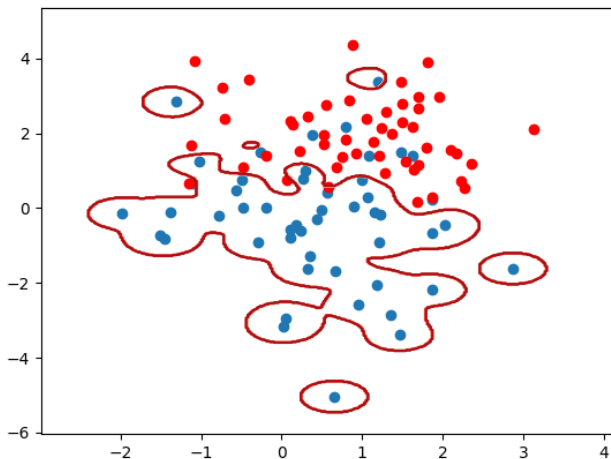


What do you think a good model would look like for this data?

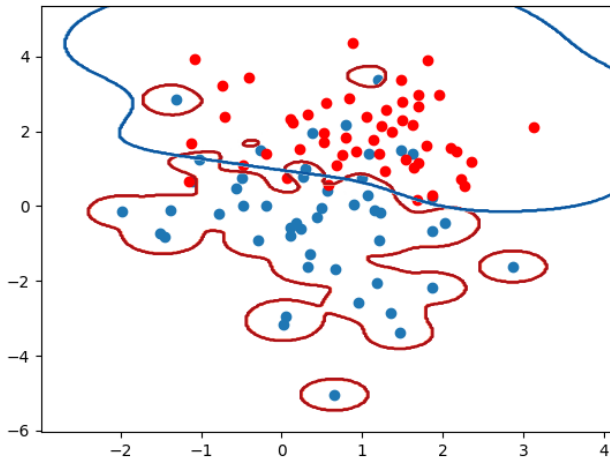
What do you think a good model would look like for this data?



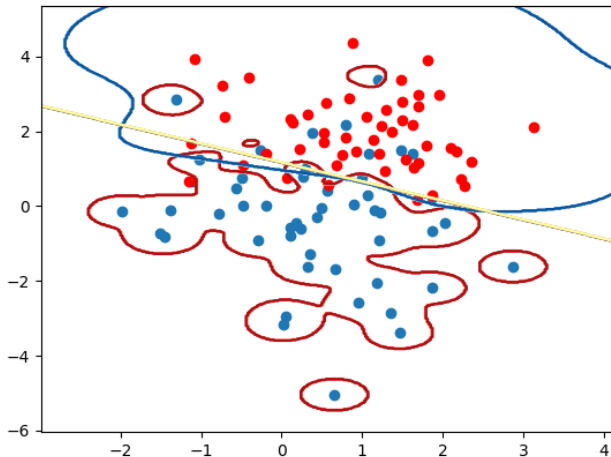
What do you think a good model would look like for this data?



What do you think a good model would look like for this data?



What do you think a good model would look like for this data?





Linear functions: a popular hypothesis class
(move on to sub-lecture 2.2)



Goldberg, Y. (2017).

Neural network methods for natural language processing.

Synthesis Lectures on Human Language Technologies, 10(1):1–309.