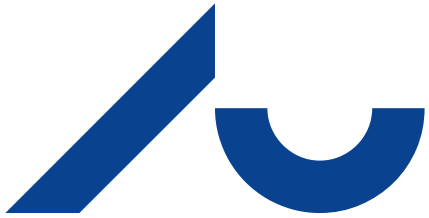

AARHUS
UNIVERSITY

Class 4: Learning From Data

Topic 1: ML Basics

Computational Analysis of Text, Audio, and Images, Fall 2023

Aarhus University

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Aarhus University

Today's Menu

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3. Create a coding scheme that, in detail, specifies how deservingness is framed as either 'deserving' or 'not deserving'
4. Manually read through articles to classify articles into the categories defined by the coding scheme

Example of Categories (Esmark and Schoop, 2017)

Table 1. Applied frames and frame dimensions: deserving and undeserving.

	Lack of incentive		Amoral behaviour	Lack of jobs	Lack of qualifications	Marginalization
Definition of problem	Lack of incentive to *work*	Lack of incentive to pursue further *education*	Lack of moral, disregard for the community	Lack of jobs	Skill set does not match current demands	Social and/ or economic marginalization
Causes	Economic structures, rational economic behaviour		Degradation of values, breakdown of norms	Economic cycles, insufficient demand and job creation	Innovation and technological development	Poverty, social, psychological and/or physical challenges
Responsibility and moral judgement	Collective responsibility for the state of the workforce Moral judgement of 'political will' to act on economic necessities		Individual responsibility for unemployment Moral judgement of individual attributes (laziness, etc.)	Collective responsibility for unemployment Moral judgement of society (solidarity, cohesiveness, etc.)	Collective responsibility for unemployment Moral judgement of society (solidarity, cohesiveness, etc.)	Collective responsibility for unemployment Moral judgement of society (solidarity, cohesiveness, etc.)
Solutions (logic of social benefits)	Reduction of benefits in order to increase incentives		Reduction of benefits as justice (punishment)	High level of social benefits as temporary compensation	High level of social benefits as means to upgrade qualifications (specific or general)	High level of social benefits reduces marginalization
	↓ Undeserving			↓ Deserving		

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- A bunch of others: weakly-supervised, semi-supervised, self-supervised, ...

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⇝ The goal of this course is to get the tools to measure politically relevant concepts using machine learning tools

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    $\rightarrow$ In reality, the model is evaluated using performance metrics – more on those in a second!

Exercise

Discuss the following questions:

1. Is the empirical loss $\hat{L}(h^*_{\mathcal{D}}, \mathcal{D})$ an unbiased estimate of the expected loss $L(h^*)$? Why/why not?
2. How can we make sure that our empirical loss is an unbiased estimate of the expected loss?

Hints: Apply what you already know about sampling theory!

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   $\rightarrow$ Test sets to the rescue!

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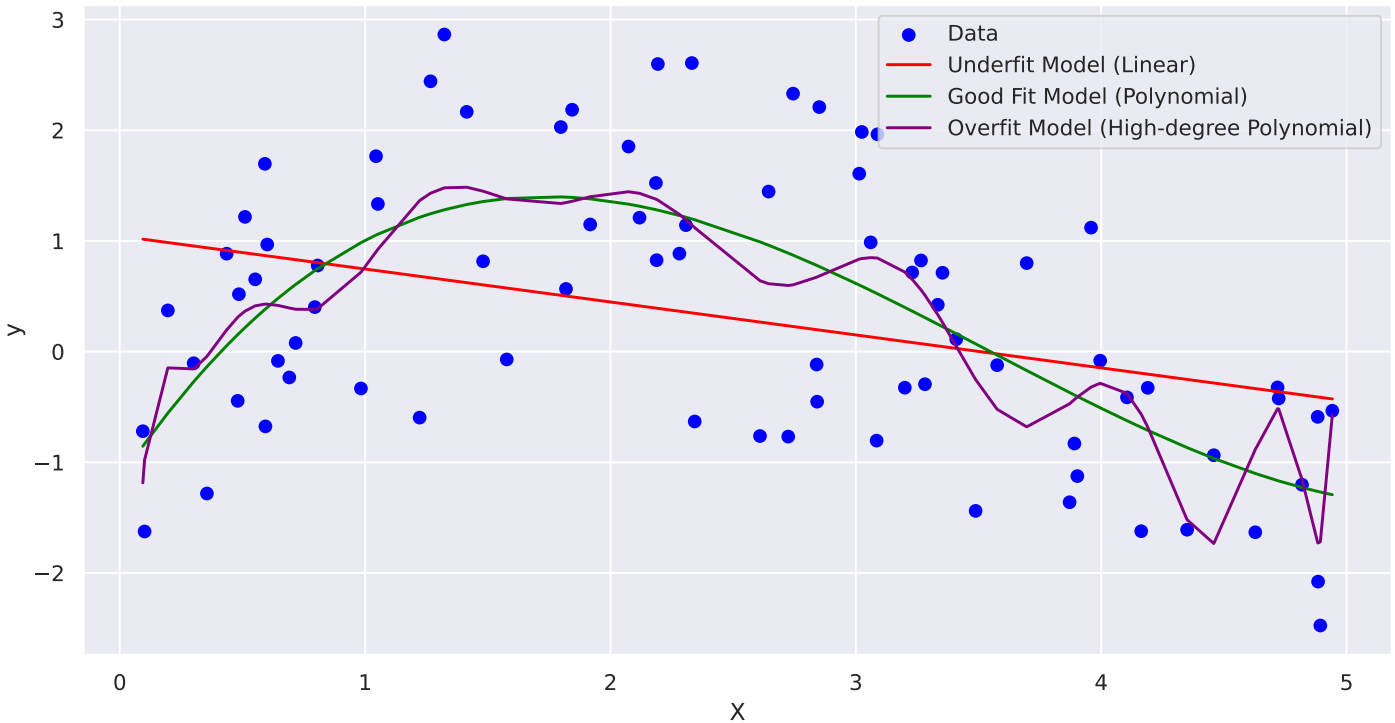
2. Underfitting: When $E_{in}(h)$ is large

Illustration of Capacity



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- Compute test loss: $\hat{L}(h^*_{\mathcal{D}_{train}}, \mathcal{D}_{test}) = E_{out}(h^*_{\mathcal{D}_{train}})$

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- Compute test error $\hat{L}(h^*_{\mathcal{D}_{val}}, \mathcal{D}_{test})$ to get an unbiased estimate of $L(h^*_{\mathcal{D}_{val}})$

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Imagine we want to find the optimal regularization parameter λ for a Lasso regression (L1-regularization):

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- Train $h_\lambda^1, h_\lambda^2, \ldots, h_\lambda^n$ on $\mathcal{D}_{train}$
- Compute validation losses: $\hat{L}(h_\lambda^1, \mathcal{D}_{val}), \ldots, \hat{L}(h_\lambda^n, \mathcal{D}_{val}) \rightarrow$ select h^* that minimizes the validation loss
- Compute test error $\hat{L}(h^*_{\mathcal{D}_{val}}, \mathcal{D}_{test})$ to get an unbiased estimate of $L(h^*_{\mathcal{D}_{val}})$

k-fold Cross-Validation

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1. Split $\mathcal{D}$ into $\{\mathcal{D}_{train}, \mathcal{D}_{test}\}$
2. Split $\mathcal{D}_{train}$ into non-overlapping folds $\mathcal{D}^1_{train}, \mathcal{D}^2_{train}, \ldots, \mathcal{D}^k_{train}$
3. For each fold $\mathcal{D}^i_{train}$ for $i \in \{1, \ldots k\}$, we train on all folds except the i-th fold
4. Compute k losses, take the average, and select $h^*_{\mathcal{D}_{val}}$
5. Compute test error $\hat{L}(h^*_{\mathcal{D}_{val}}, \mathcal{D}_{test})$

	Fold 1	**Fold 2**	**Fold 3**	**Fold 4**	**Fold 5**
Split 1	Validation	Train	Train	Train	Train
Split 2	Train	Validation	Train	Train	Train
Split 3	Train	Train	Validation	Train	Train
Split 4	Train	Train	Train	Validation	Train
Split 5	Train	Train	Train	Train	Validation

Table 1: 5-Fold Cross-Validation

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- In what cases does the accuracy fall short?

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Supervised Algorithms

- Linear models (e.g. linear or logistic regression)
- Support Vector Machines (SVMs)
- Naive Bayes
- Trees
- Neural nets
- . . .

→ All have excellent support using scikit-learn

Estimating Probabilities From Classification

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Protest Dynamics (Steinert-Threlkeld et al. 2022)

Figure 1. *A*, Sample images and the protest classifier's rating of them. *B*, Protest images with their state violence rating. *C*, Protest images' protester violence rating. Labels specify each image's city and label probability. The use of hard negatives in the training set ensures that scenes that contain crowds (*A*, *left*), individuals walking on streets (*C*, *left*), or a nonprotest sign (*A*, *second*) are not included in analysis. Color version available as an online enhancement.

Polarization (Peterson and Spirling 2018)

PA

Classification Accuracy as a Substantive Quantity of Interest: Measuring Polarization in Westminster Systems

Andrew Peterson[1] and Arthur Spirling[2]

[1] *Postdoctoral Researcher, University of Geneva, Switzerland. Email: andrew.peterson@unige.ch*
[2] *Associate Professor of Politics and Data Science, New York University, USA. Email: arthur.spirling@nyu.edu*

Abstract

Measuring the polarization of legislators and parties is a key step in understanding how politics develops over time. But in parliamentary systems—where ideological positions estimated from roll calls may not be informative—producing valid estimates is extremely challenging. We suggest a new measurement strategy that makes innovative use of the "accuracy" of machine classifiers, i.e., the number of correct predictions made as a proportion of all predictions. In our case, the "labels" are the party identifications of the members of parliament, predicted from their speeches along with some information on debate subjects. Intuitively, when the learner is able to discriminate members in the two main Westminster parties well, we claim we are in a period of "high" polarization. By contrast, when the classifier has low accuracy—and makes a relatively large number of mistakes in terms of allocating members to parties based on the data—we argue parliament is in an era of "low" polarization. This approach is fast and substantively valid, and we demonstrate its merits with simulations, and by comparing the estimates from 78 years of House of Commons speeches with qualitative and quantitative historical accounts of the same. As a headline finding, we note that contemporary British politics is approximately as polarized as it was in the mid-1960s—that is, in the middle of the "postwar consensus". More broadly, we show that the technical performance of supervised learning algorithms can be directly informative about substantive matters in social science.

Keywords: statistical analysis of texts, polarization, learning

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Recast $\mathcal{D}$ as a X_{ij} matrix with dimensions $N \times M$:

- i: Row index
- j: Column index
- x_i: Row i
- x_j: Column j

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2. *Exploration*: Getting to know your data

Discovery of Legislative Styles (Sulkin et al. 2017)

WILLIAM BERNHARD
University of Illinois
DANIEL SEWELL
University of Iowa
TRACY SULKIN
University of Illinois

A Clustering Approach to Legislative Styles

Once elected to office, members of Congress (MCs) face choices about how to prioritize their activities. What is the right balance between working in the district and on Capitol Hill? How active will they be in introducing and cosponsoring legislation? Will they give speeches and interviews? On which issues will they focus their attention? With whom will they collaborate and form coalitions? How much time will they spend raising money? To what extent will they toe the party line or chart their own course? Collectively, these decisions make up a member of Congress's "legislative style." Legislators' styles are central to congressional life, with the potential to shape their career trajectories, the representation they provide to constituents, and the nature of the policies passed by Congress.

In this article, we analyze legislative style, testing our theory about its correlates and consequences. We focus on the 1,049 legislators who served in the 101st–110th Congresses (1989–2008), gathering data on the activities of members of Congress, categorizing these into indices that reflect components of legislative style, and using longitudinal

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- PCA
- t-SNE
- UMAP

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Discuss an application for which PCA could be used to identify latent dimensions.

What Makes Party Systems Different? (Magyar 2021

PA

What Makes Party Systems Different? A Principal Component Analysis of 17 Advanced Democracies 1970–2013

Zsuzsanna B. Magyar

University of Lucerne, Lucerne, Switzerland. Email: zmagyar@ucla.edu

Abstract

Party systems, that is, the number and the size of all the parties within a country, can vary greatly across countries. I conduct a principal component analysis on a party seat share dataset of 17 advanced democracies from 1970 to 2013 to reduce the dimensionality of the data. I find that the most important dimensions that differentiate party systems are: "the size of the biggest two parties" and the level of "competition between the two biggest parties." I use the results to compare the changes in electoral and legislative party systems. I also juxtapose the results to previous party system typologies and party system size measures. I find that typologies sort countries into categories based on variation along both dimensions. On the other hand, most of the current political science literature use measures (e.g., the effective number of parties) that are correlated with the first dimension. I suggest that instead of these, indices that measure the opposition structure and competition could be used to explore problems pertaining to the competitiveness of the party systems.

Keywords: principal component analysis, party system, typology, effective number of parties

Results (Magyar 2021)

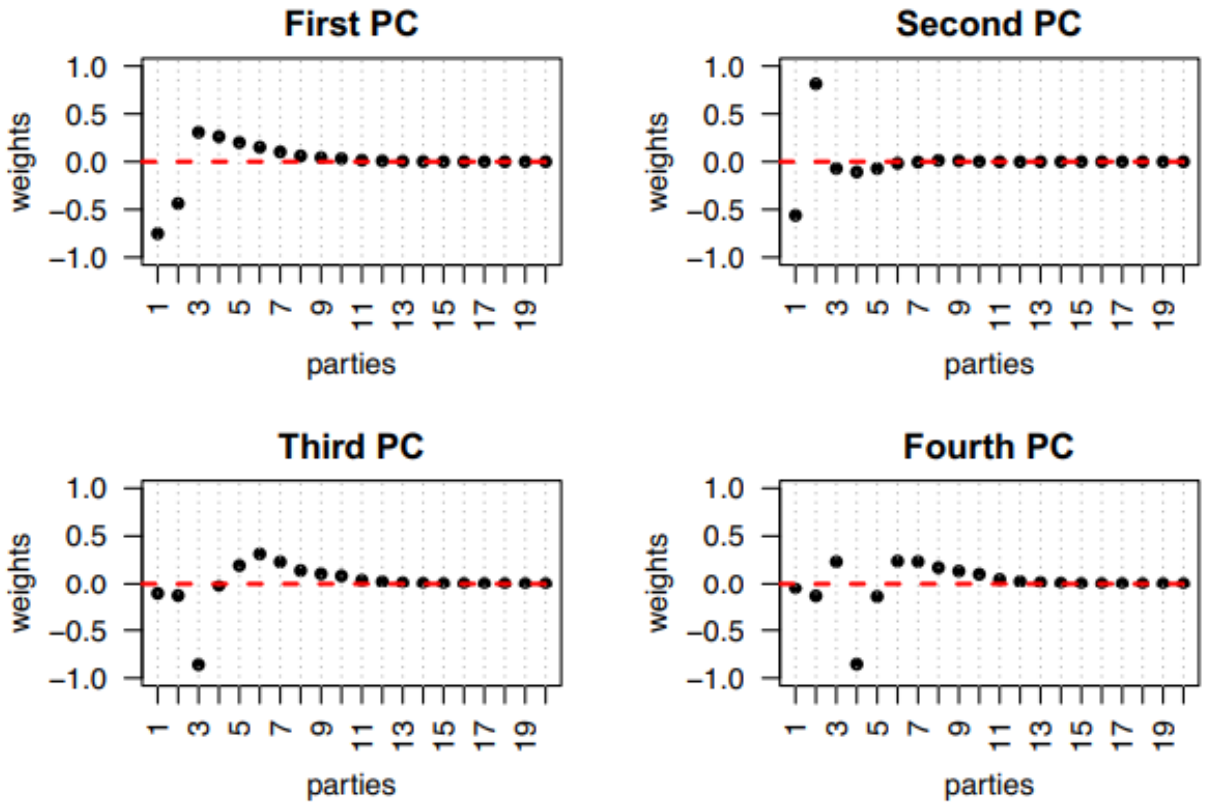

Figure 1. Loadings, PCA.*Notes:* The plot shows the loadings, the weight of parties in determining the principal components in the PCA.

Compound Measures (Abramson et al. 2022

Historical Border Changes, State Building, and Contemporary Trust in Europe

SCOTT F ABRAMSON *University of Rochester, United States*
DAVID B. CARTER *Washington University in St. Louis, United States*
LUWEI YING *University of California, Los Angeles, United States*

Political borders profoundly influence outcomes central to international politics. Accordingly, a growing literature shows that historical boundaries affect important macro-outcomes such as patterns of interstate disputes and trade. To explain these findings, existing theories posit that borders have persistent effects on individual-level behavior, but the literature lacks empirical evidence of such effects. Combining spatial data on centuries of border changes in Europe with a wide range of contemporary survey evidence, we show that historical border changes have persistent effects on two of the most politically significant aspects of behavior: individuals' political and social trust. We demonstrate that in areas where borders frequently changed, individuals are, on average, less trusting of others as well as their governments. We argue that this occurs because border changes disrupt historical state-building processes and limit the formation of interpersonal social networks, which leads to lower levels of trust.

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From ML to DL

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where $\sigma(\cdot)$ is the sigmoid function:

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When we input x, what do we get out? A (smooth) probability bounded between 0 and 1

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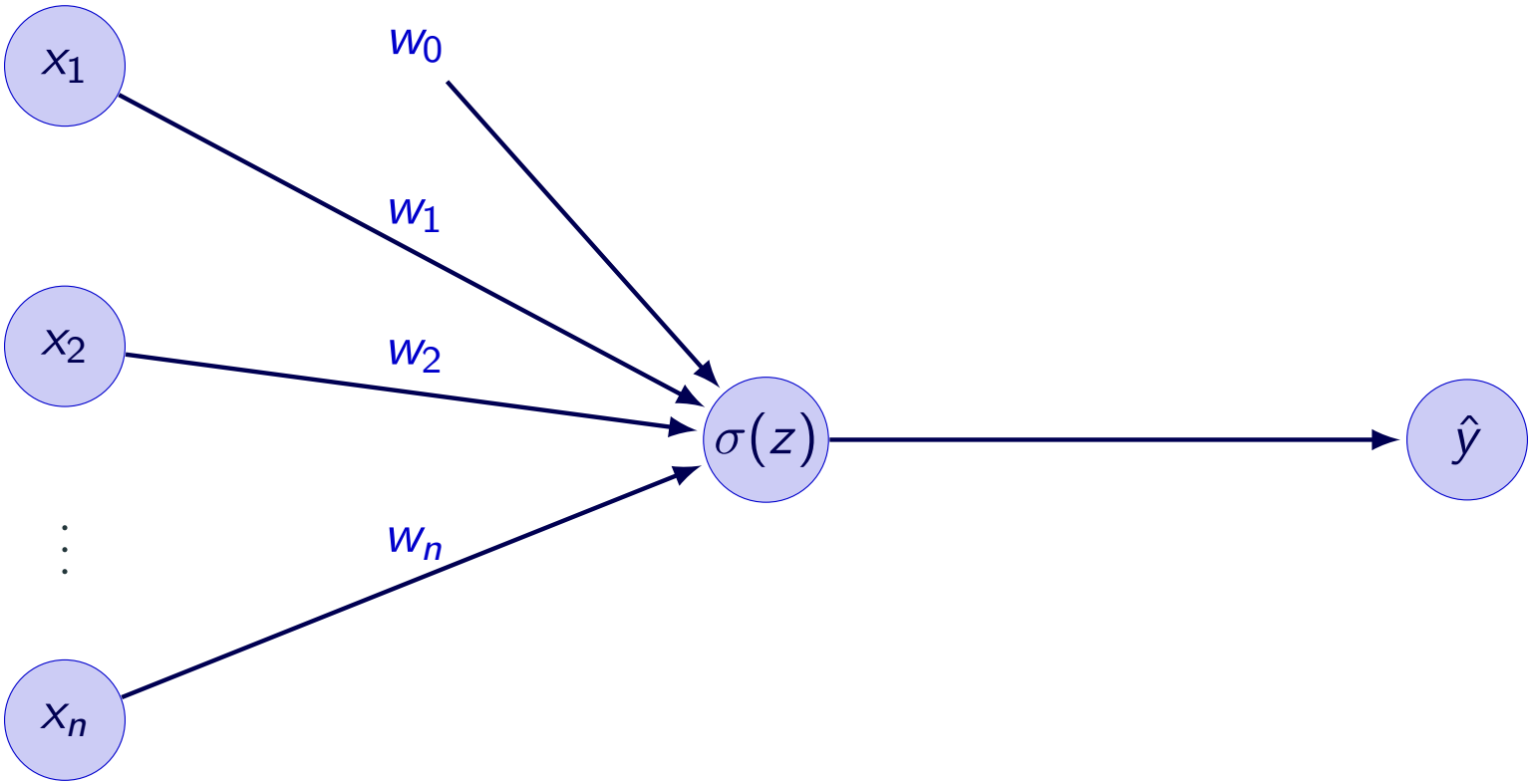
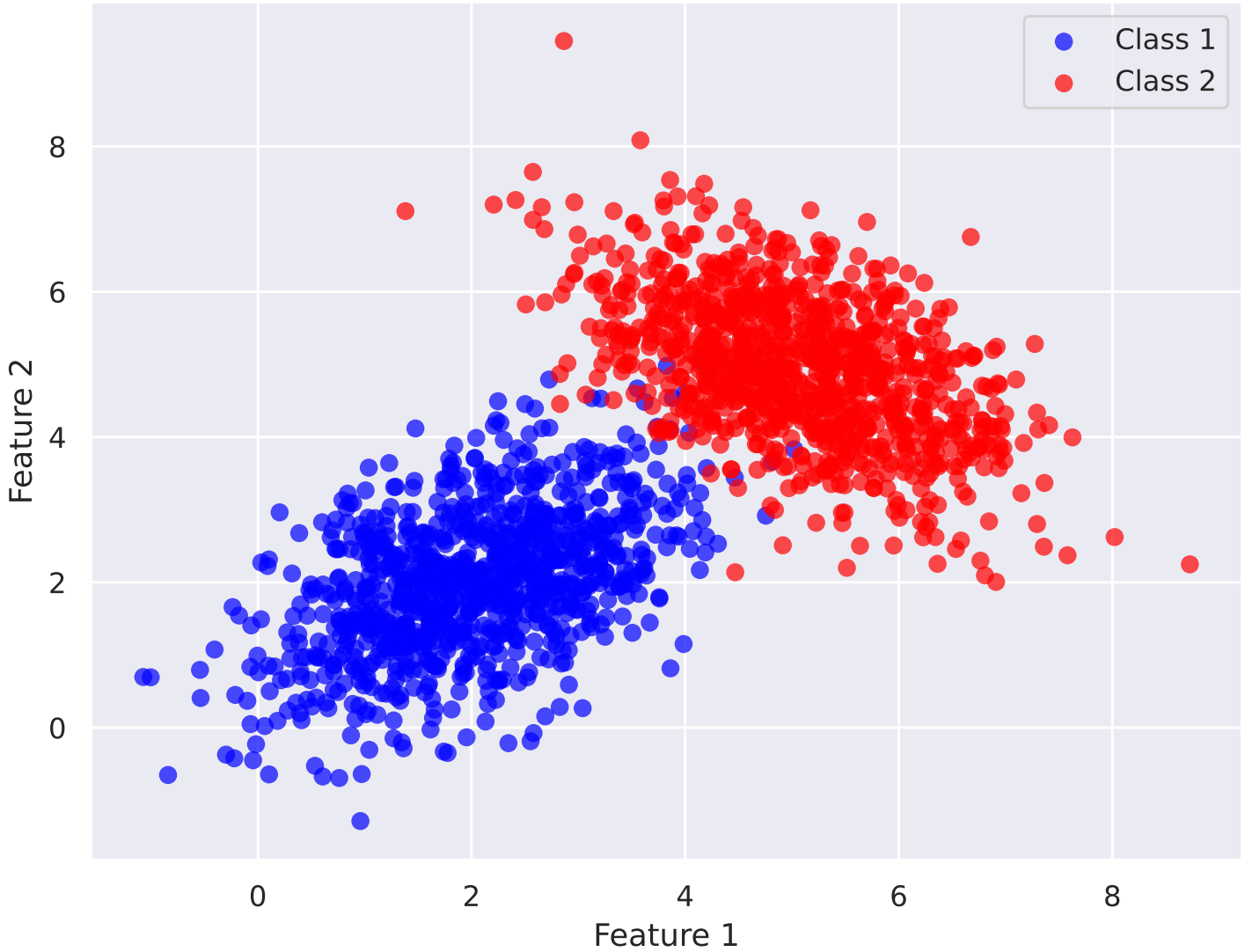
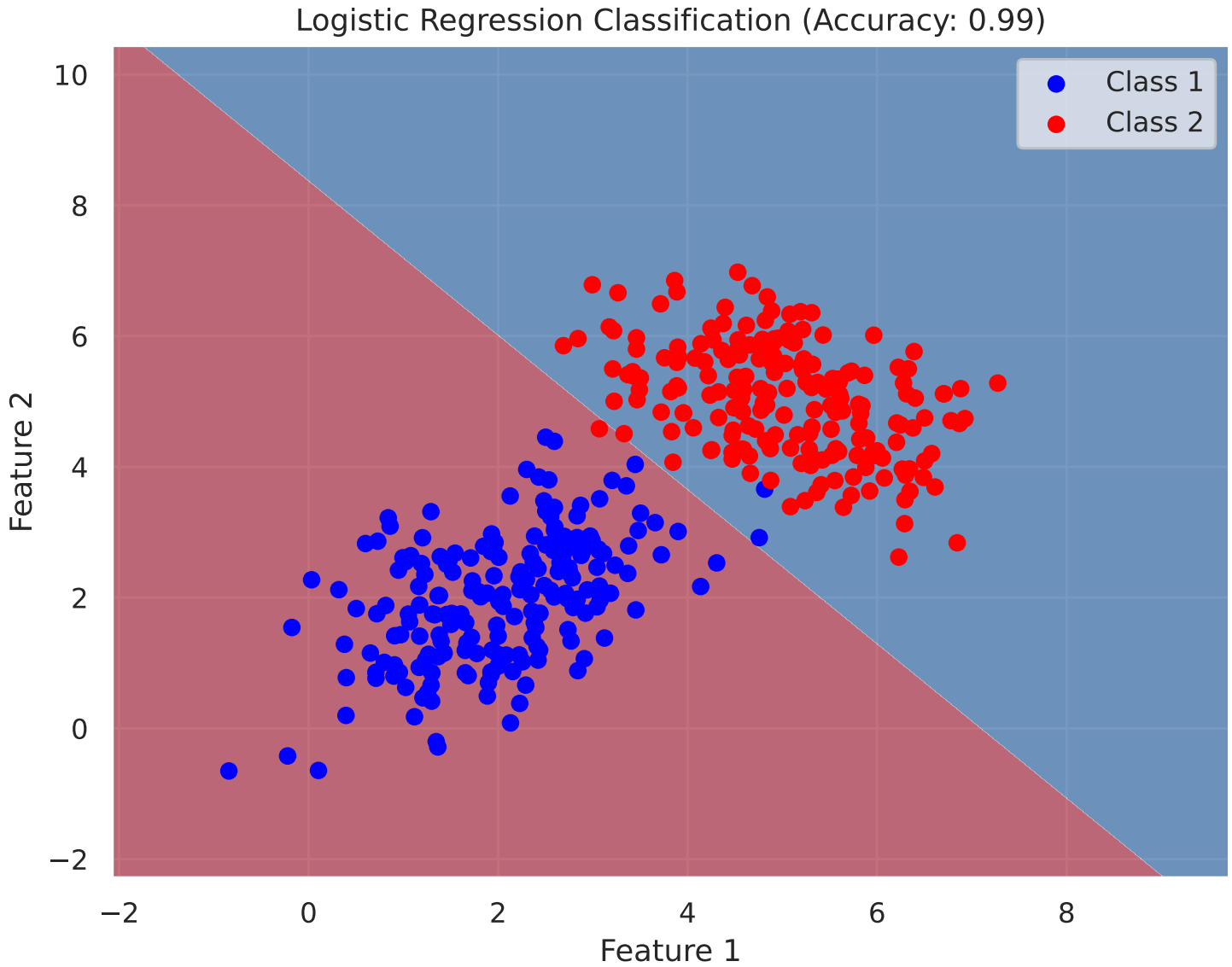


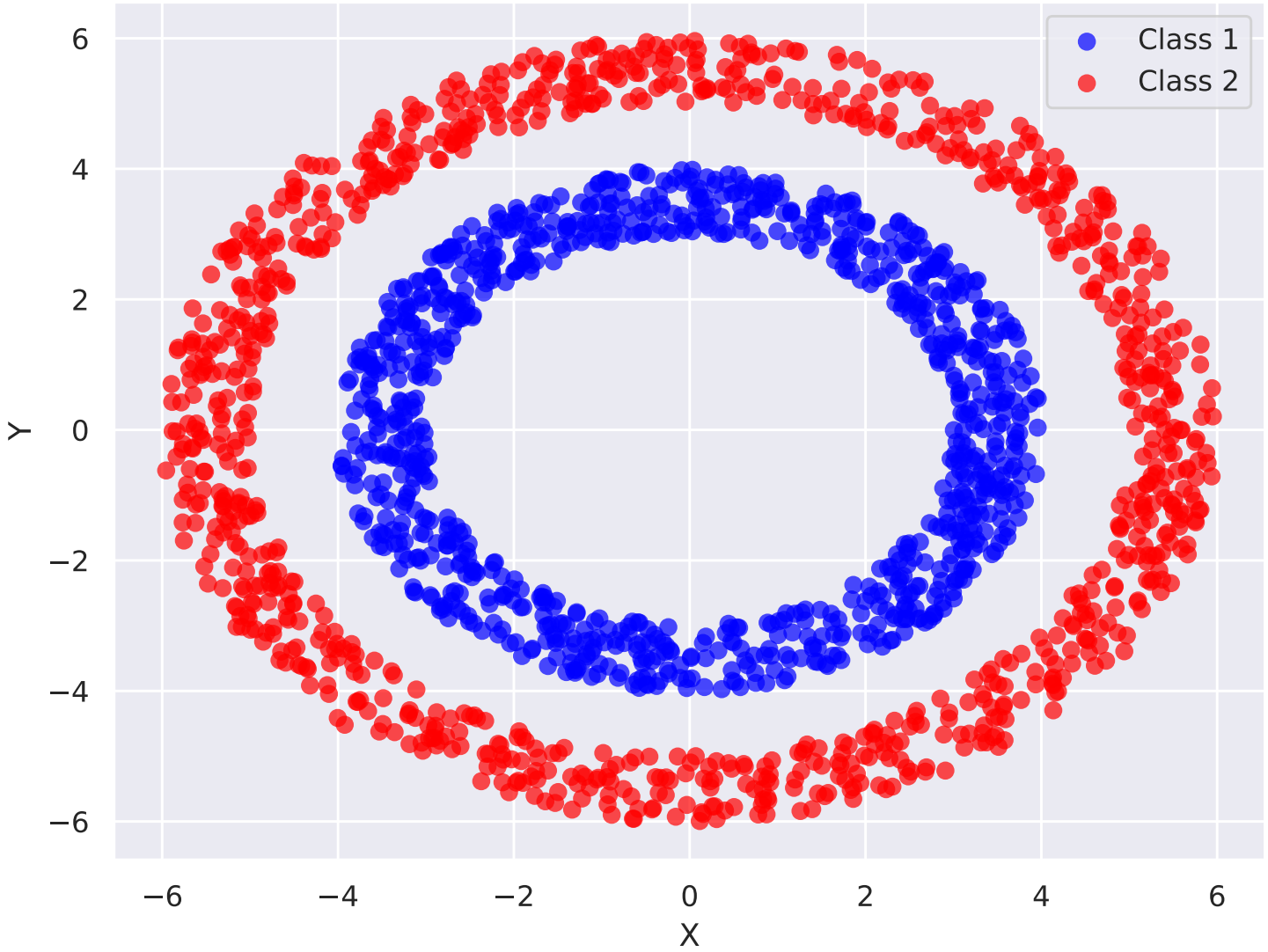
Linear Separable Data



Decision Boundary



Non-linear Separable Data



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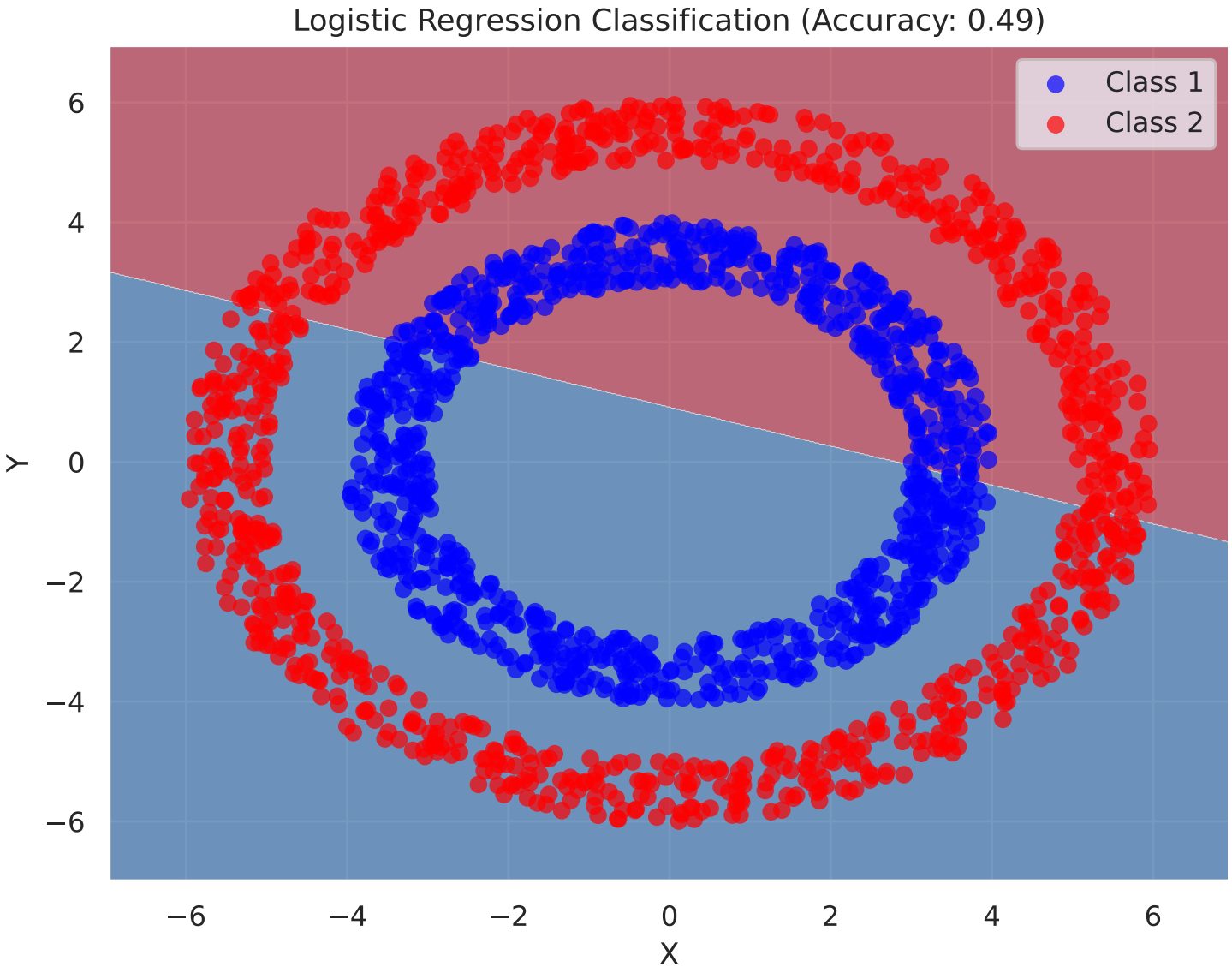

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- Find weights using backpropagation and gradient descent (not important for us)
- BUT: Prone to overfitting!

Neural Network Diagram

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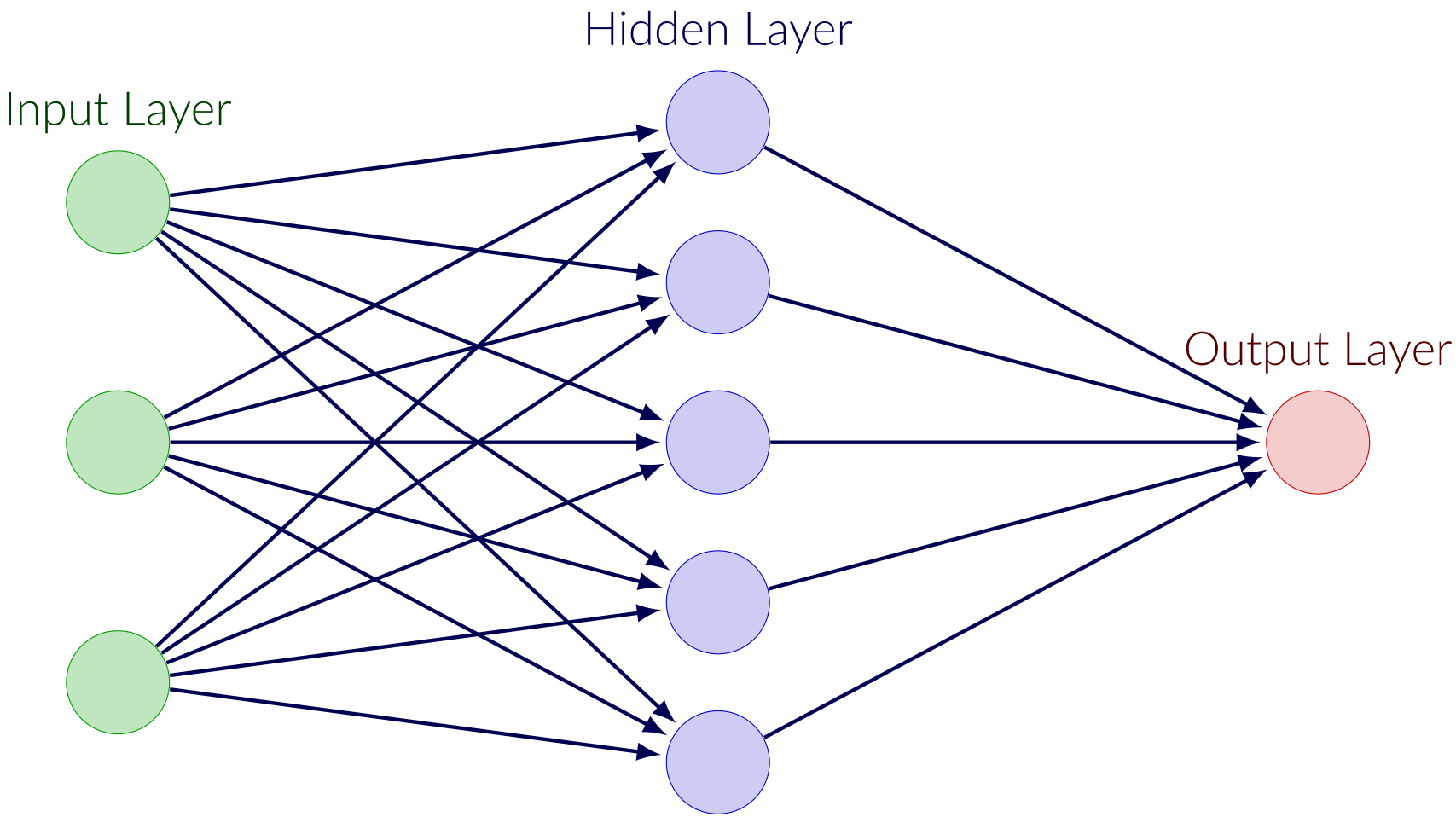

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$$
\begin{aligned}
h_1 &= \sigma(w_{11}x_1 + w_{21}x_2 + w_{31}x_3 + b_1) \\
h_2 &= \sigma(w_{12}x_1 + w_{22}x_2 + w_{32}x_3 + b_2) \\
h_3 &= \sigma(w_{13}x_1 + w_{23}x_2 + w_{33}x_3 + b_3) \\
h_4 &= \sigma(w_{14}x_1 + w_{24}x_2 + w_{34}x_3 + b_4) \\
h_5 &= \sigma(w_{15}x_1 + w_{25}x_2 + w_{35}x_3 + b_5) \\
\hat{y} &= \sigma(w_{y1}h_1 + w_{y2}h_2 + w_{y3}h_3 + w_{y4}h_4 + w_{y5}h_5 + b_y)
\end{aligned}
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We will primarily use the fully-connected layers and convolution nets.

See you next week!

Topic 1: ML Basics

Computational Analysis of Text, Audio, and Images, Fall 2023

Aarhus University