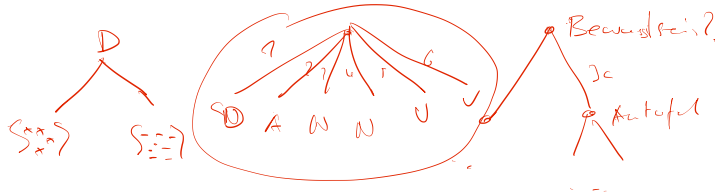
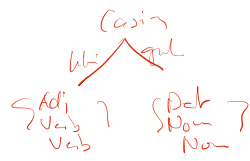
Recap



Decision Tree

- Classification algorithm
- Built around trees, recursive learning and prediction
- Pros
  - Highly transparent (if the number of features is not very large)
  - Reasonably fast
  - Dependencies between features can be incorporated into the model
- Cons
  - No pairwise dependencies
  - May lead to overfitting
  - Only nominal features
- Variants exist



UNIVERSITÄT
ZU KÖLN

Machine Learning, Part 2
(= Deep Learning)

Einführung in die Informationsverarbeitung

Nils Reiter

November 9, 2023

INSTITUT FÜR
DIGITAL HUMANITIES
UNIVERSITÄT ZU KÖLN

Introduction: Neural Networks

- The machinery behind ChatGPT & co
- Old idea, but rediscovered in late 00s
- Basic idea: A (mathematical) function that takes input, does some computation, produces output
  - E.g.: $f(x_1, x_2, x_3) = 0.5x_1 - 0.7x_2 + 0.1x_3 + 0.2$

Intuition

x_1	x_2	y
2	2	3
2	4	8
3	4	8,2
⋮		⋮

$y = (x_1 + x_2 + 2)/2$

$y = 2 + \frac{2}{2} = x_1 + \frac{x_2}{2} = x_1 + 0{,}5x_2$

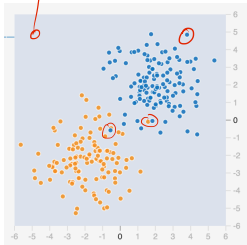
$y = 0{,}5 \cdot x_1 + x_2$

Allowed operations:
Addition, Subtraction, Multiplication

$y = \ldots x_1 + \ldots x_2 + \ldots$

$y = 0{,}2x_1 + 2{,}5x_2 - 2{,}4$

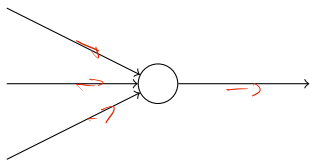
More complex example



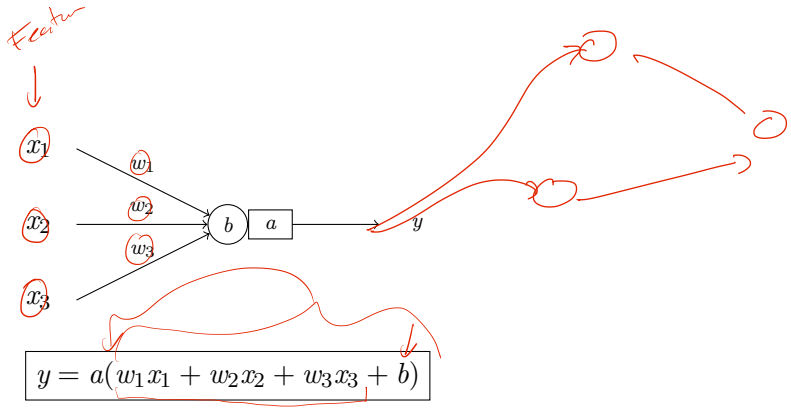
- We have collected data for a binary classification (indicated by colors)
- Our goal: Estimate a function that takes in x_1 and x_2 values and outputs probabilities for classes orange and blue
  - E.g., x_1: word length, x_2: position in a sentence, output: is the word a noun?

Neural Network Playground (runs in your browser!)

A Neuron

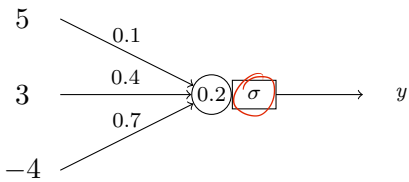


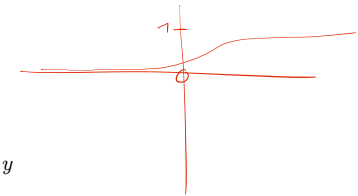
A Neuron



A Neuron

Example

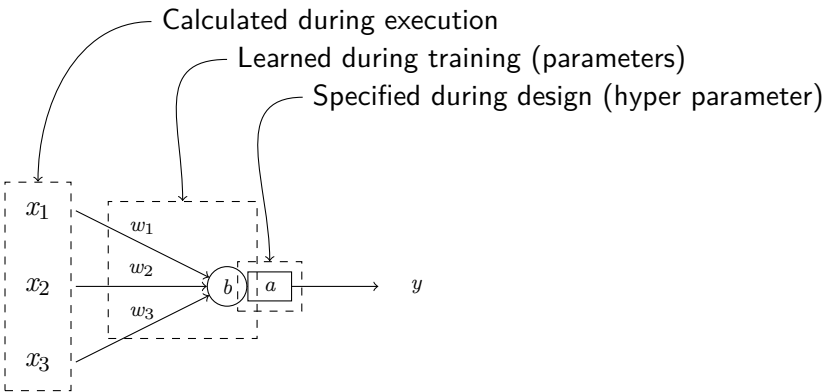




$$
\begin{aligned}
y &= a(w_1x_1 + w_2x_2 + w_3x_3 + b) \\
&= \sigma(0.1 \times 5 + 0.4 \times 3 + 0.7 \times -4 + 0.2) \\
&= \sigma(-0.9) \\
&= 0.28905049737499603653 69
\end{aligned}
$$

A Neuron

Where do these values come from?



Many Neurons make a Network

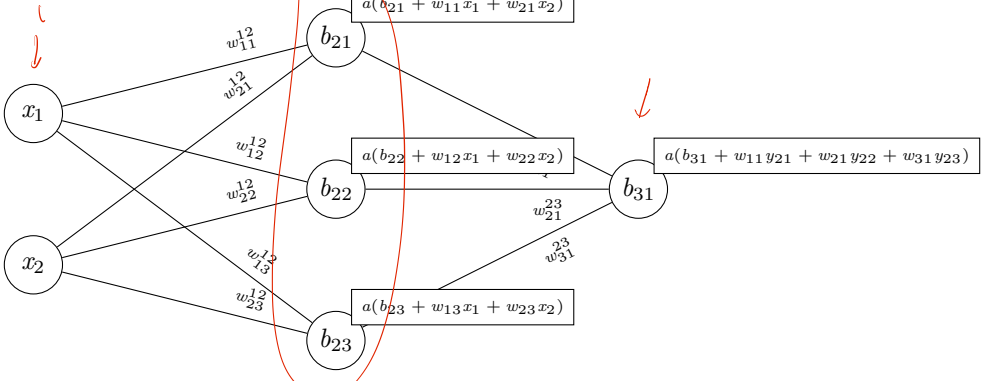


Figure: A simple neural network with 1 hidden layer

Prediction Model

"Forward Pass"

- If we have all the weights, bias terms, numbers of neurons and layers, we can compute the output of the network
  - Conceptually: Applying functions to calculate individual values in sequence

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- Practically, a lot of the computation happens in matrices in parallel
  - Hidden layer
    - Weights: $W_{1,2} = \begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \end{bmatrix}$
    - Biases $B_2 = (b_{21}, b_{22}, b_{23})$

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- Hidden layer computation: $f_2(X) = \sigma(\underbrace{W_{1,2}^{\intercal} X + B_2}_{\text{matrix operations}})$
- Deep learning involves a lot of matrix operations
  - GPUs are highly optimized for this
  - Hint: Gaming-GPUs that support CUDA are also usable for deep learning

Feed-Forward Neural Networks

- The above is called a "feedforward neural network"
  - Information is fed only in forward direction

Feed-Forward Neural Networks

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  - Information is fed only in forward direction
- Configuration/design choices
  - Activation function in each layer
  - Number of neurons in each layer
  - Number of layers

Learning Algorithm

- We can immediately calculate outcomes (= make predictions), even if all weights are generated randomly
- How do we improve the weights?

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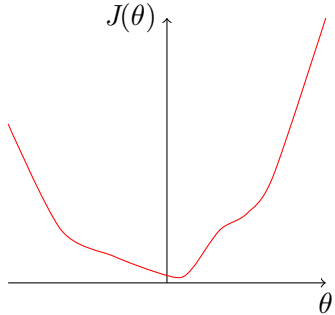
- We can immediately calculate outcomes (= make predictions), even if all weights are generated randomly
- How do we improve the weights?
- Gradient Descent
  1. Initialize all weights randomly
  2. Calculate and derive the loss (the 'wrongness') of the current weights on the training data
  3. Check if we have found the optimal solution
  4. If not, calculate the direction in which the loss decreases
  5. Go back to 3.

Loss function: Intuition

- Loss should be as small as possible
- Total loss can be calculated for given parameters θ
  - θ is a vector containing all weights and bias terms in the network
- Idea:
  - We change θ until we find the minimum of the function
  - We use the derivative to find out if we are in a minimum
  - The derivative also tells us in which direction to go

Loss function: Intuition



Loss and Hypothesis Function

- Hypothesis function h
  - Calculates outcomes, given feature values x
  - Done by the neural network
- Loss function J
  - Calculates 'wrongness' of h, given parameter values θ (and a data set)
  - In reality, θ represents millions of parameters

Processing Language

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Word Indices

1. Establish the vocabulary (i.e., the set of all known tokens [in the training corpus])
2. Create a ranking (i.e., count all word types)
3. Decide on a threshold (e.g., the $10\,000$ most frequent words)
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$\Rightarrow$ "Out of vocabulary" (OOV) words are a challenge for applications

Word2Vec

Literature basis

Two very influential papers by Mikolov et al.

Tomáš Mikolov/Kai Chen/Greg Corrado/Jeffrey Dean (2013). "Efficient Estimation of Word Representations in Vector Space". In: *arXiv cs.CL*. URL: https://arxiv.org/pdf/1301.3781.pdf

Tomáš Mikolov/Ilya Sutskever/Kai Chen/Greg S Corrado/Jeff Dean (2013). "Distributed Representations of Words and Phrases and their Compositionality". In: *Advances in Neural Information Processing Systems 26*. Ed. by C. J. C. Burges/L. Bottou/M. Welling/Z. Ghahramani/K. Q. Weinberger. Curran Associates, Inc., pp. 3111–3119. URL: http://papers.nips.cc/paper/5021-distributed-representations-of-words-and-phrases-and-their-compositionality.pdf

Software package

word2vec – https://github.com/tmikolov/word2vec
(other implementations do exist)

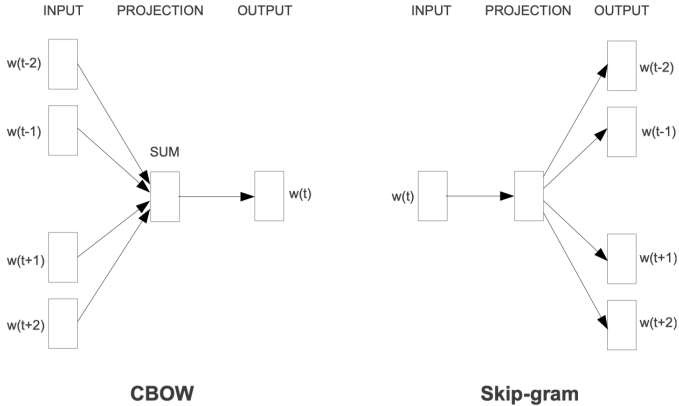
Word2Vec

Core Idea

- Define a classification task for which we have huge training data sets
  - Given a word, predict predict possible context words
  - Training data: Any text collection (e.g., Wikipedia)
- Train a neural network
- Extract learned weights and use as embeddings ☑

Word2Vec

Two tasks



Continuous Bag of Words (CBOW)

Context words used to predict a single word

Skip-Gram

One word used to predict its context

Word2Vec

Skip-gram

- Context: ± 2 words around target word t

```
... lemon, a [tablespoon of apricot jam, a] pinch ...
             c1          c2 t       c3   c4
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- Classifier:
  - Predict for (t, c) wether c are *really* context words for t
  - In other words: Probability of $\vec{t}$ and $\vec{c}$ being positive examples: $p(+|\vec{t}, \vec{c})$

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  - "a word is likely to occur near the target if its embedding is similar to the target embedding"

Jurafsky/Martin (JM19, 112)

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  - Similarity $\rightarrow$ probability? Mathematical conversion

Summary

- Neural Networks
  - Many individual neurons in combination
  - During training weights will be adapted, until best approximation to training data is reached
  - Prediction: Application of weights, i.e., multiplication and addition
- Word2Vec
  - Use a neural network to predict wether two words are really appearing together in texts
  - Extract learned weights as embeddings
  - Leads to embeddings that are similar, if the words appear in similar contexts
    - E.g., Berlin and Paris appear in the contexts of country capital

References I

- Jurafsky, Dan/James H. Martin (2019). *Speech and Language Processing*. 3rd ed. Draft of October 16, 2019. Prentice Hall.
- Mikolov, Tomáš/Kai Chen/Greg Corrado/Jeffrey Dean (2013). "Efficient Estimation of Word Representations in Vector Space". In: *arXiv cs.CL*. URL: https://arxiv.org/pdf/1301.3781.pdf.
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