Recap: Machine Learning

Naive Bayes

- Probabilistic method for classification
- Naive because we ignore feature dependencies
- Prediction model:

$$\arg\max_{c \in C} p(c|f_1, f_2, \ldots, f_n)$$

- Training: Count relative frequencies

Logistic Regression

- Regression method for binary classification
- Output numbers as probabilities
- Prediction model:

$$\frac{1}{1 + e^{-(ax+b)}}$$

- Training: Gradient descent with loss function

Neural Network

- Layered architecture
- Classification type depends on last layer
- Output numbers as probabilities
- Prediction model:

$$L_n(L_{n-1}(L_{\ldots}(L_1(X))))$$

- Training: Backpropagation w/ loss function

Last Week

```python
import numpy as np
from tensorflow import keras
from tensorflow.keras import layers
from sklearn.preprocessing import LabelBinarizer

# create a random data set with 500 pairs
# of random numbers
x_train = np.random.randn(100,5)

# Target value: What's the maximum of five numbers?
# (0.1, 0.2, -0.2, 0.5, -3)
# -> (4)
y_train = np.array([(np.argmax(x)) for x in x_train])

# one-hot-encoding of target values
lb = LabelBinarizer()
y_train = lb.fit_transform(y_train)

# setup the model architecture
model = keras.Sequential()
model.add(layers.Input(shape=(5,)))
model.add(layers.Dense(20, activation="sigmoid"))
model.add(layers.Dense(5, activation="softmax"))

# compile it
model.compile(loss="categorical_crossentropy",
  optimizer="sgd",
  metrics=["accuracy"])

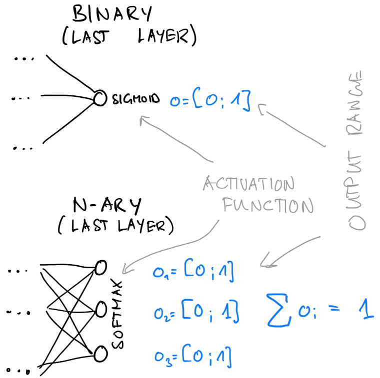
# train it
model.fit(x_train, y_train, epochs=20, batch_size=1)

# create a test data set
x_test = np.random.randn(100,5)
y_test = np.array([np.argmax(x) for x in x_test])
model.evaluate(x=x_test, y=lb.fit_transform(y_test))
```

- Task: Given five numbers, give us the index of the highest (5-ary classification task)
- 20 epochs, stochastic gradient descent, categorical cross entropy
- 77 % Accuracy

Binary and N-Ary Classification / One-Hot-Encoding

CLASSIFICATION



ONE-HOT-ENCODING

- VECTOR TO REPRESENT OUTPUT NUMBER

EXAMPLE

- TRAINING INSTANCE

  CATEGORY 2 (OF 3): $\begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$

- TEST OUTPUT

  CATEGORY 2: $\begin{bmatrix} 0.1 \\ 0.7 \\ 0.2 \end{bmatrix}$

- LOSS CALCULATED BETWEEN $\begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$ AND $\begin{bmatrix} 0.1 \\ 0.7 \\ 0.2 \end{bmatrix}$

Hausaufgabe 3

Trainieren Sie ein logistisches Regressionsmodell, um handgeschriebene Ziffern zu erkennen. Die Ziffern wurden handgeschrieben, schwarz/weiß eingescannt und die Bilder dann als 28x28-Matritzen mit Graustufeninformationen bereitgestellt. Es handelt sich nur um Nullen und Einsen, und ist damit eine binäre Klassifikationsaufgabe. Sie finden die Trainings- und Testdaten hier, und hier ein Python-Skript, mit einer Funktion zum Einlesen der Daten. Verwenden Sie die Bibliothek scikit-learn für das eigentliche Training (und schauen Sie sich ruhig ein bisschen um, was die Bibliothek sonst so bereithält).

- Wie hat's geklappt?
- Was kam raus?
- Gab es Schwierigkeiten oder Überraschungen?

→ Hausaufgabe 4: Ziffernerkennung mit neuronalem Netz und einigen selbstgeschriebenen Ziffern

UNIVERSITÄT ZU KÖLN

Machine Learning: How to use Neural Networks with Words
Word Embeddings

VL Sprachliche Informationsverarbeitung

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Introduction

A very simple text example

- Task: Given a sentence (with four words), predict wether the sentence is positive or negative
  - E.g., a comment about a book or movie

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- Task: Given a sentence (with four words), predict wether the sentence is positive or negative
  - E.g., a comment about a book or movie
- Operationalization
  - Binary classification task
  - Four input features, one for each word
    - Each word gets an index number, which will be the input of the network

demo

s10-example-01.py

Lessons Learned

- Representing words by index numbers alone is not satisfactory
- `{'awesome': 4, 'is': 5, 'terrible': 6, 'bad': 7, 'super': 8}`
    - 'Terrible' and 'bad' are semantically much closer than 'terrible' and 'awesome', but this is not represented
    - Replacing 'bad' with 'terrible' or 'super' is both a change of 1 index position, but has very different meaning

What is Semantics at all?

Man kann für eine ***große*** *Klasse von Fällen der Benützung des Wortes* ***Bedeutung*** *– wenn auch nicht für* ***alle*** *Fälle seiner Benützung – dieses Wort so erklären: Die Bedeutung eines Wortes ist sein Gebrauch in der Sprache.* *(Wittgenstein, 1953)*

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You shall know a word by the company it keeps (Firth, 1957, 11)

Distributional Semantics

Count vectors

- For each word, we count how often it appears with all other words (within a window of n tokens)
- Results in very long vectors, because all other words
- Many words do not appear with many other words, because of Zipf
  - Many elements are zero

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Variants of count vectors

- TF-IDF instead of raw counts
- Mathematical dimensionality reduction

Count Vectors in Our Example

- Words used in similar contexts often get similar vectors
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Count Vectors in Our Example

- Words used in similar contexts often get similar vectors
  - E.g., evaluative adjectives like ‘awesome’, ‘super’, ...
  - Antonyms often also get similar vectors
- Recipe
  - Take a large corpus
  - Extract count vectors
  - Insert vectors into our training set

Section 2

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 (NIPS 2013)*. 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`
    Originally published on "Google Code"

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- No interpretable dimensions
- Dense vectors: No zeros, and much fewer dimensions than in count vectors

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- Recap: Logistic/linear regression and gradient descent
  - Algorithm to fit parameters to a distribution of data points
  - Core ingredient: Loss function
  - Result: Parameter setting θ

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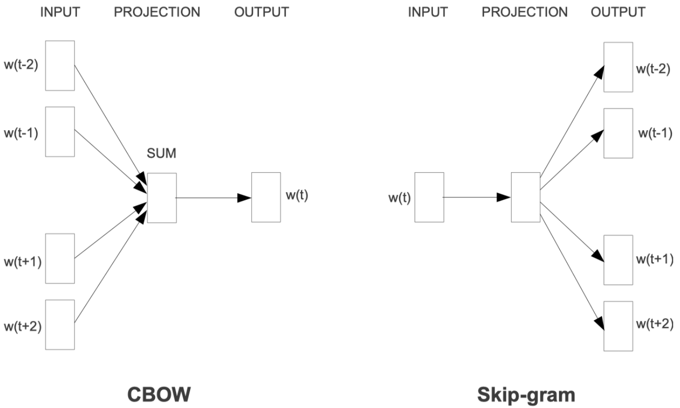
  - Core ingredient: Loss function
  - Result: Parameter setting θ
- Word2vec
  - Let's use these parameters as word vectors
    - (one parameter vector per word)
  - How to come up with a task that generates these parameters?

Two tasks



Continuous Bag of Words (CBOW)	Skip-Gram
Context words used to predict one word	One word used to predict its context

Skip-gram

- Context: ± 2 words around target word t

```
... dogs, such as a German Shepherd or a Labrador, ...
               c1 c2  t        c3    c4
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- Classifier:
  - Predict for (t, c) wether c are *really* context words for t
  - Probability of $\vec{t}$ and $\vec{c}$ being positive examples: $p(+|\vec{t}, \vec{c})$

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  - Probability of $\vec{t}$ and $\vec{c}$ being positive examples: $p(+|\vec{t}, \vec{c})$
- Vector similarity $\rightarrow$ probability
  - Similarity of vectors? Dot product 🡇
  - Cosine similarity $\rightarrow$ probability? Logistic function ✔
  - "a word is likely to occur near the target if its embedding is similar to the target embedding"

Jurafsky/Martin (2023, 18 f.)

When are vectors similar?

- Operation that takes two vectors and returns a similarity score
- Linear algebra: dot product
  - A.k.a. scalar product, inner product, Skalarprodukt, Punktprodukt, inneres Produkt

$$\begin{aligned}\vec{a} \cdot \vec{b} &= |\vec{a}||\vec{b}| \cos \sphericalangle(\vec{a}, \vec{b}) \\ &= \sum_{i=1}^{N} a_i b_i\end{aligned}$$

Skip-gram

Notation
t, c: words
$\vec{t}$, $\vec{c}$: vectors for the words

$$
\begin{aligned}
p(+|t, c) &= \frac{1}{1+e^{-\vec{t}\cdot\vec{c}}} = \sigma(\vec{t}\cdot\vec{c}) \\
p(-|t, c) &= 1 - \frac{1}{1+e^{-\vec{t}\cdot\vec{c}}} = \frac{e^{-\vec{t}\cdot\vec{c}}}{1+e^{-\vec{t}\cdot\vec{c}}} = 1 - \sigma(\vec{t}\cdot\vec{c})
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but the context consists of more than one word!

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$$p(+|t,c_{1:k}) = \prod_{i=1}^{k} \frac{1}{1+e^{-\vec{t}\cdot\vec{c}_i}}$$

$$\log p(+|t,c_{1:k}) = \sum_{i=1}^{k} \log \frac{1}{1+e^{-\vec{t}\cdot\vec{c}_i}}$$

Skip-gram

- So far, we have assumed that we have vector $\vec{t}$ for word t, but where do they come from?
- Basic gradient descent: We start randomly, and iteratively improve

Skip-gram

Negative sampling

- Negative examples
  - Training a classifier needs negative examples, i.e., words that are not in the context of each other

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  - For every positive tuple (t, c), we add k negative tuples
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- New 'parameter' k on this slide
  - Different status than θ (the parameters we want to learn)
  - Therefore: Hyperparameters

Word2Vec

Loss

- We also need a loss function
- Idea:
  - Maximize
    - $p(+|t, c)$ (positive samples), and
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$$L(\theta) = \sum_{(t,c)} \log p(+|t,c) + \sum_{(t,c_n)} \log p(-|t,c_n)$$

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θ: Concatenation of all $\vec{t}$, $\vec{c}$, $\vec{c}_n$

Remarks and observations

- Each word is used twice, with different roles
  - As target word (for predicting its context)
  - As context word (to be predicted from another target word)
  - Different options: Only use one embedding, combine them by addition or concatenation

Section 3

Embeddings and Neural Networks

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- Option 2
  - Train your own embeddings in your neural network
  - In the end, it's just more parameters to learn, and we know how to do that
  - Keras: `keras.layers.Embedding`

demo

s10-example-02.py, s10-example-03.py

Section 4

Summary

Summary

Represent text data in neural networks

- Map words to indices
- Embeddings
  - Way to represent input data
  - Word2Vec: Concrete method to calculate/train embeddings
  - Well suited as input for neural networks
  - Pre-trained embeddings
    - Easy to use
    - Trained on very large corpora
    - Allow to incorporate some kind of knowledge into our own models that we don't have to annotate