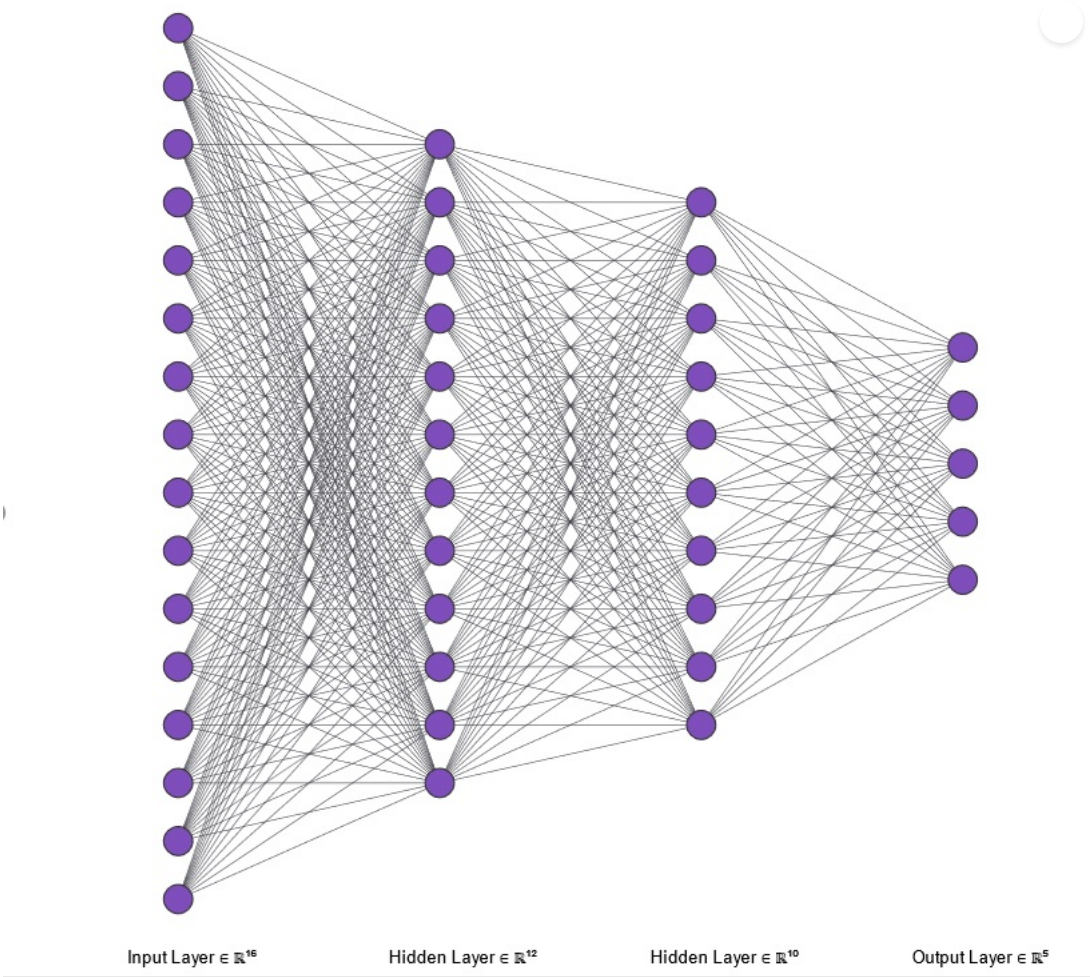
Sequenzvorhersage

Künstliche Neuronale Netz (ANN)

Dabei handelt es sich um einen Deep-Learning-Algorithmus, der Informationen auf ähnliche Weise wie das menschliche Gehirn verarbeitet. Es wird häufig verwendet, um das Muster zwischen den Eingabemerkmalen und der entsprechenden Ausgabe in einem Datensatz zu erstellen und zu lernen. Die nächste Abbildung zeigt die Architektur des neuronalen Netzwerks:

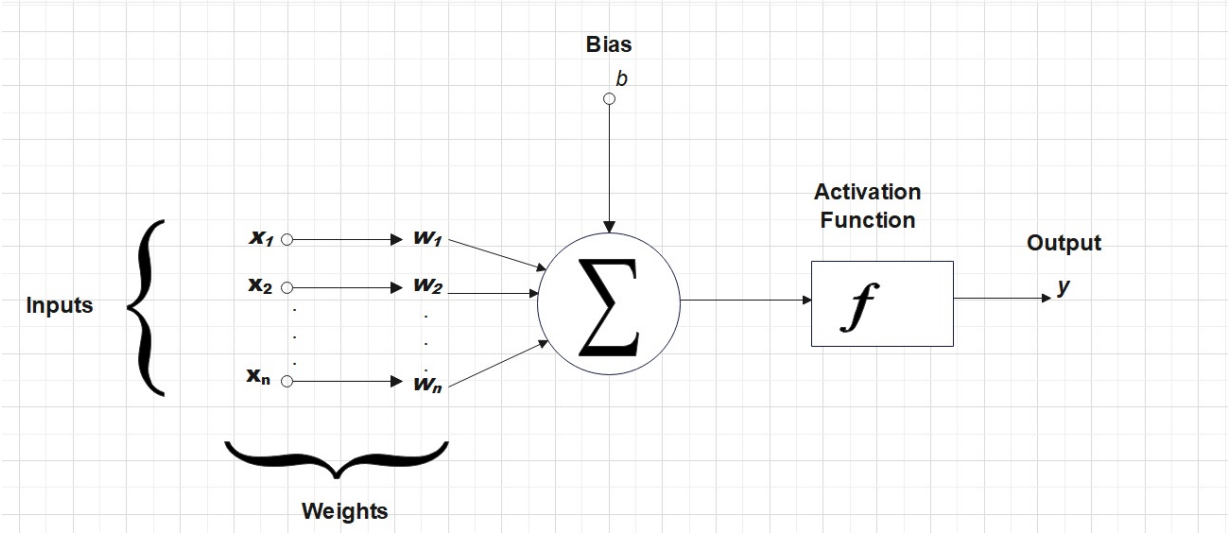


Die erste Schicht besteht aus einer Reihe von Neuronen. Diese Ebene sollte die gleiche Größe wie der Eingabevektor xi haben, wobei i = 1, 2, ….., D, der die Merkmale des Datensatzes darstellt. Die verborgenen Schichten haben die Aufgabe, mathematische Berechnungen an der Eingabe durchzuführen, um die Ausgabe zu erzeugen, die an die Ausgabeschicht weitergeleitet werden soll. In einem neuronalen Klassifizierungsnetzwerk sollte die Dimension der Ausgabeschicht der Anzahl der Klassen oder Beschriftungen im Datensatz in einem neuronalen Klassifizierungsnetzwerk entsprechen. Beispielsweise erfordert ein Datensatz mit 4 Merkmalen und 3 Klassen ein neuronales Netzwerk mit 4 Eingabeneuronen und 3 Ausgabeneuronen, um das Eingabe- und Ausgabemuster zu lernen.
Der Algorithmus des neuronalen Netzwerks umfasst zwei Schritte:

1. Vorwärtsdurchlauf von Daten durch ein Feed-Forward-Neuronales Netzwerk.
2. Rückausbreitung von Fehlern zum Trainieren eines neuronalen Netzwerks.

1. Vorwärtsdurchlauf durch ein Feed-Forward-Neuronales Netzwerk:

Bei dieser Methode werden die Informationen über die verborgenen Schichten an die Ausgabeschicht des Netzwerks weitergeleitet. Die Neuronen der ersten verborgenen Schicht erhalten eine gewichtete Summe von Werten des Eingabevektors zusammen mit einem Bias-Term b, wie in Abb. 2 dargestellt. Anschließend wendet jedes Neuron eine differenzierbare, nichtlineare Aktivierung auf diese gewichtete Summe an, um einen Ausgabewert zu ergeben . Diese Schritte sind in der folgenden Abbildung dargestellt:



Ebenso verwenden Neuronen nachfolgender Schichten eine gewichtete Summe der Ausgaben aller Neuronen der vorherigen Schicht zusammen mit einem Bias-Term als Eingabe. Dieser Prozess wird fortgesetzt, bis die Neuronen der Ausgabeschicht ihre Ausgabewahrscheinlichkeitswerte der Klassen bereitstellen. Dem Eingabevektor wird eine Klasse zugewiesen, deren entsprechendes Neuron den höchsten Wahrscheinlichkeitswert hat.

In einem neuronalen Netzwerk verfügt jede Schicht über eine eigene Aktivierungsfunktion. Die für ChatBot verwendeten Aktivierungsfunktionen sind beispielsweise die Rectified Linear Unit (ReLu)-Funktion für verborgene Schichten und die Softmax-Funktion für die Ausgabeschicht. Die ReLu-Funktion ist definiert als:

$$f(x) = \begin{cases} 0, if\ x < 0 \\ x, if\ x \geq 0 \end{cases}$$

Und die Softmax-Funktion ist definiert als:

$$\sigma(\vec{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}$$

Wobei Vektor Z der Eingabevektor, e^{z_i} Standard-Exponentialfunktion für Eingabevektor, K die Anzahl der Klassen im Mehrklassenklassifikator, e^{z_j} Standard-Exponentialfunktion für Ausgabevektor der Klasse j.

2. Fehlerrückausbreitung zum Trainieren eines neuronalen Netzwerks:

Dieser Schritt ist der wichtigste, da die Hauptaufgabe des Algorithmus des neuronalen Netzwerks darin besteht, den richtigen Satz von Gewichten für alle Schichten zu lernen, die zur richtigen Ausgabe führen. Dies beinhaltet die Weitergabe des am Ausgang berechneten Fehlers oder Verlusts nach hinten, sodass die neuen Gewichte und Verzerrungen gelernt werden.

In neuronalen Netzen werden je nach Modelltyp zwei Haupttypen von Verlustfunktionen verwendet:

1. Regressionsverlustfunktionen: Mittlerer quadratischer Fehler, mittlerer absoluter Fehler. Es werden in der Regression neuronale Netze eingesetzt.
2. Klassifizierungsverlustfunktionen: Binäre Kreuzentropie, kategoriale Kreuzentropie. Diese Art von Verlustfunktion wird für Klassifizierungsaufgaben verwendet.

Im Folgenden sind die Formeln der MSE- und Kreuzentropieverlustfunktionen aufgeführt:

$$\text{MSE} = \frac{1}{n}\sum_{i=0}^{n}(\hat{y}_i - y_i)^2$$

MSE ist der Durchschnitt der quadrierten Differenzen zwischen den tatsächlichen und den vorhergesagten Werten.

Für die Klassifizierung mehrerer Klassen, bei der die Anzahl der Klassen M > 2 beträgt, wird die kategoriale Kreuzentropie verwendet:

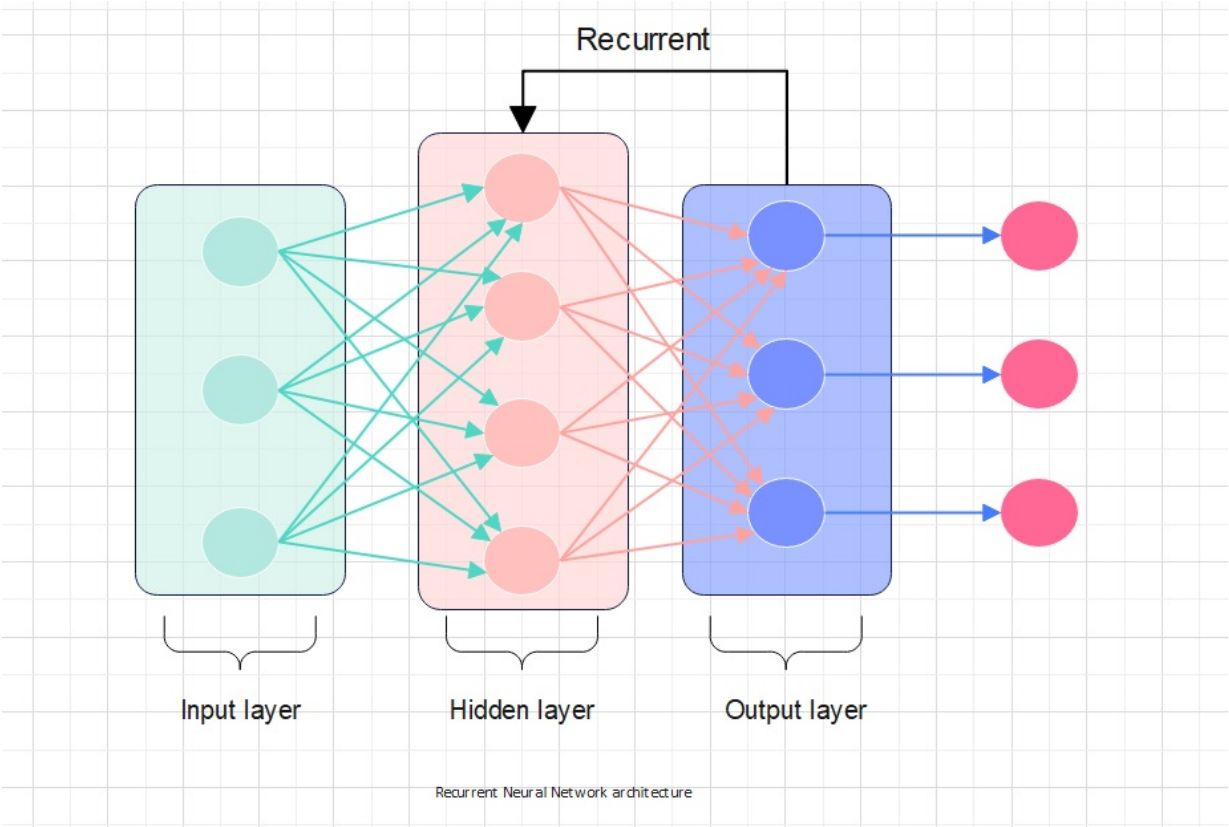
$$\text{CE loss} = -\sum_{c=1}^{M} y_{o,c} \log\left(p_{o,c}\right)$$

„Loss Functions — ML Glossary documentation (ml-cheatsheet.readthedocs.io)“

$y_{o,c}$ nimmt 1 an, wenn die Beobachtung o der Klasse c ist, andernfalls 0. $P_{o,c}$ ist die vorhergesagte Wahrscheinlichkeit, dass die Beobachtung o aus der Klasse c stammt.

Rekurrente Neuronale Netze (RNN):

Standardmäßige künstliche neuronale Netze sind nicht in der Lage, die zeitliche Abhängigkeit zwischen Proben zu erfassen. Um solche historischen Datenpunkte einzubeziehen, wurden rekurrente neuronale Netze (RNN) angepasst, um zukünftige Werte durch Modellierung vergangener Informationen vorherzusagen. RNN ist eine Variante eines künstlichen neuronalen Netzwerks, das mit einem Mechanismus zum Umgang mit sequentiellen Daten oder Zeitreihen ausgestattet ist, in denen Datenpunkte eine zeitliche Korrelation aufweisen. Die RNN-Architektur verfügt über einen „Speicher“, der ihnen hilft, die Zustände früherer Eingaben zu speichern und sie zur Berechnung zukünftiger Prognosen der Sequenz zu verwenden.

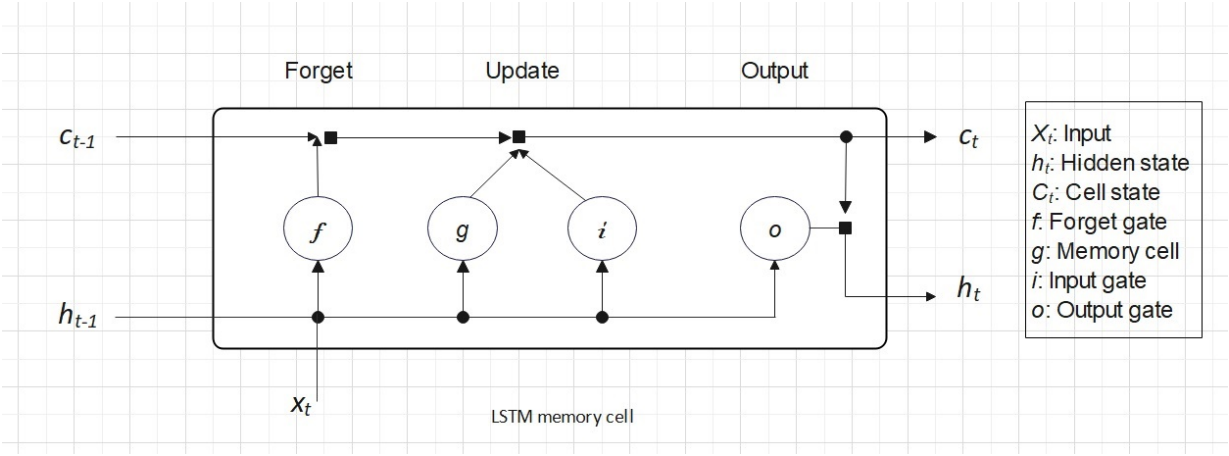


LSTM:

LSTM-Netzwerke sind eine Sonderform der RNN-Architektur, bei der eine Einheit (oder ein Neuron) zyklische Verbindungen enthält. Der Hauptunterschied zwischen einer LSTM-Entität und einer Standard-RNN-Entität besteht darin, dass LSTM aus sogenannten Gates besteht, die den Informationsfluss durch die Entität besser regulieren sollen. Das Hauptproblem von RNNs liegt in ihrer begrenzten Fähigkeit, längerfristige Abhängigkeiten zu lernen. Standard-RNNs können nicht lernen, wenn es aufgrund eines „verschwindenden“ oder „explodierenden“ Gradienten zu Zeitverzögerungen von mehr als 5 bis 10 diskreten Zeitschritten zwischen relevanten Eingabeereignissen und Zielsignalen kommt. Ein verschwindender Gradient tritt auf, wenn der Wert des Produkts der Ableitung abnimmt, bis sich irgendwann die partielle Ableitung der Verlustfunktion einem Wert nahe Null nähert, was ihre Fähigkeit, langfristige Beziehungen zu lernen, verringert. LSTM-Netzwerke gehen dieses Problem an, indem sie einen konstanten Fehlerfluss durch „Constant Error Carrousels“ (CECs) innerhalb spezieller Einheiten, sogenannter Zellen, erzwingen. Eine LSTM-Zelle enthält zwei Gatter, die lernen, auf den Fehlerfluss im CEC jeder Speicherzelle zuzugreifen. Das multiplikative Eingabegatter schützt den CEC vor Störungen durch irrelevante Eingaben. Ebenso schützt das multiplikative Ausgangsgatter andere Einheiten vor Störungen durch aktuell irrelevante Speicherinhalte. Diese zusätzlichen Tore ermöglichen es dem Netzwerk, langfristige Beziehungen zwischen

Datenpunkten effektiver zu lernen.

Aufgrund der geringeren Empfindlichkeit gegenüber der Zeitlücke eignen sich LSTM-Netzwerke besser für die sequentielle Datenanalyse als einfache RNNs. Zusätzlich zum verborgenen Zustand von RNNs verfügt die Architektur für einen LSTM typischerweise über eine Speicherzelle, ein Eingangs-Gate, ein Ausgangs-Gate und ein Oblivion-Gate, wie unten gezeigt:

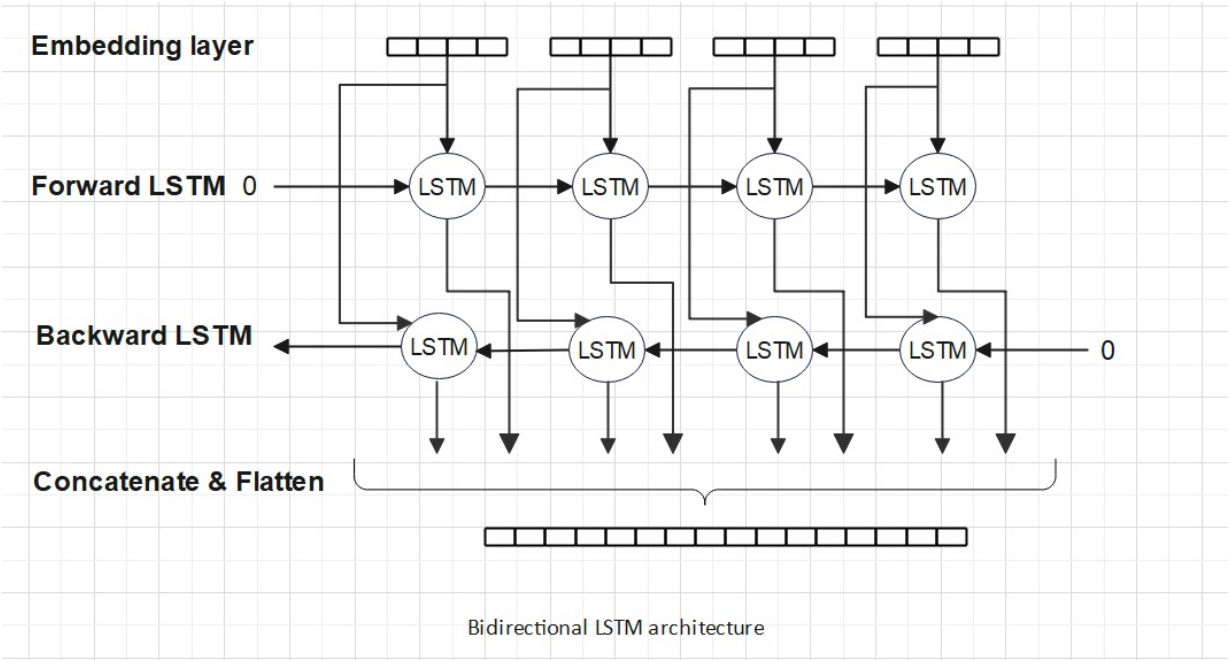


Dabei ist h der verborgene Zustand, der das Kurzzeitgedächtnis darstellt, c der Zellzustand, der das Langzeitgedächtnis darstellt, und x die Eingabe. Die Gewichtungen und Bias des Eingangsgatters steuern das Ausmaß, in dem ein neuer Wert in die Zelle fließt. In ähnlicher Weise steuern die Gewichtungen und Bias des Vergessens-Gates und des Ausgangs-Gates, welche Daten in der Zelle verbleiben und welche Daten zur Berechnung der Ausgangsaktivierung des LSTM-Blocks verwendet werden.

Im Gegensatz zum Standard-LSTM fließt die Eingabe bei bidirektionalem LSTM in beide Richtungen, da wir eine zusätzliche Ebene zum Trainieren der Umkehrung der Eingabesequenz haben. bidirektionales lstm ist ein leistungsstarkes Werkzeug zur Modellierung der sequentiellen Abhängigkeiten zwischen Wörtern und Phrasen in beiden Richtungen der Sequenz. Da zum Trainieren der Daten zwei Ebenen verwendet werden, muss die Ausgabe beider zusammengeführt werden. Der Zusammenführungsmechanismus kann eine der folgenden Funktionen haben:

1. Summe
2. Multiplikation
3. Mittelung
4. Verkettung (Standard)

Hier wird eine Einbettungsschicht verwendet, um eine Folge von Wortindizes in Einbettungsvektoren abzubilden, sodass das Netzwerk mehr über die Beziehung zwischen Wörtern erfahren kann.



Sequenzvorhersage Übung

Für das Training des bidirektionalen LSTM-Modells verwenden Twitter Datensatz hier .
Wir müssen den Text zeilenweise trennen, damit wir mithilfe des Tokenizers Sequenzen aus dem Text generieren können.
Lasst uns zunächst die Daten importieren und einen Blick darauf werfen:

In [8]:
```
import pandas as pd
import numpy as np
import heapq
import matplotlib.pyplot as plt
from nltk.tokenize import word_tokenize
from keras.models import Sequential, load_model
from keras.layers.core import Dense, Activation
from keras.layers import LSTM


from tensorflow.keras.layers import Embedding, LSTM, Dense, Bidirectional, Dropout
from keras.optimizers import RMSprop
from tensorflow.keras.preprocessing.text import Tokenizer


#path ='text.txt'
path = 'en_US.twitter.txt'
# read and convert from one block text into a list of lines
with open(path, encoding='utf-8') as f:
     lines = [line.rstrip('\n') for line in f]


text =lines[:5000]
```

In [16]:
```
text[:5]
```

Out[16]:
```
['How are you? Btw thanks for the RT. You gonna be in DC anytime soon? Love to see you. Been way, way too long.',
 "When you meet someone special... you'll know. Your heart will beat more rapidly and you'll smile for no reason.",
 "they've decided its more fun if I don't.",
 'So Tired D; Played Lazer Tag & Ran A LOT D; Ughh Going To Sleep Like In 5 Minutes ;)',
 'Words from a complete stranger! Made my birthday even better :)']
```

Der erste Schritt besteht darin, die Wörter in den Texten zu tokenisieren, was bedeutet, den Text in eine Folge von ganzen Zahlen umzuwandeln (wobei jede ganze Zahl der Index eines Tokens in einem Wörterbuch ist). Dann müssen wir aus unserem Text ein n_gram-Modell erstellen. Ein n-Gramm ist eine zusammenhängende Folge von n Elementen aus einer bestimmten Text- oder Sprachprobe. Bei der Sprachmodellierung werden Unabhängigkeitsannahmen getroffen, sodass jedes Wort nur von den letzten n − 1 Wörtern abhängt. Dies hilft dem LSTM-Modell, den Kontext zu verstehen und die Beziehungen zwischen Wörtern zu lernen.

In [32]:
```
#oov_token: if given, it will be added to word_index and used to replace out-of-vocabulary words during text_to_sequence calls
# For those words which are in the vocab
#the first step is to tokenize the words in the texts ,
#which means turning the text  into  a sequence of integers
# (each integer being the index of a token in a dictionary).
# then we need to build n_gram model from our text. an n-gram  is a contiguous sequence of n items
# from a given sample of text or speech. in  language modeling,
# independence assumptions are made so that each word depends only on the last n - 1 words.
# this help lstm model to understand the context and to learn the relationships between words.
tokenizer = Tokenizer(oov_token='<oov>')
tokenizer.fit_on_texts(text['title'])
total_words = len(tokenizer.word_index) + 1
input_sequences = []
for line in text['title']:
    token_list = tokenizer.texts_to_sequences([line])[0]
    for i in range(1, len(token_list)):
        n_gram_sequence = token_list[:i+1]
        input_sequences.append(n_gram_sequence)

print("Total input sequences: ", len(input_sequences))
```

Die Eingabesequenzen müssen dieselbe Länge haben, daher verwenden wir die Auffülltechnik, um jeder Zeichenfolge Nullen hinzuzufügen, sodass sie dieselbe Länge wie die längste Sequenz in der Liste haben.

In [10]:
```
# sequence padding
from tensorflow.keras.preprocessing.sequence import pad_sequences
max_sequence_len = max([len(x) for x in input_sequences])
input_sequences = np.array(pad_sequences(input_sequences, maxlen=max_sequence_len, padding='pre'))
input_sequences[1]
```

Out[10]:
```
array([ 0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,
        0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0,  0, 54, 22,  6])
```

Als nächstes müssen wir Eingabedaten des Modells vorbereiten. Hier verwenden wir das letzte Wort in jeder Sequenz als das vom Modell vorherzusagende Wort, während der Rest für das Training verwendet wird.

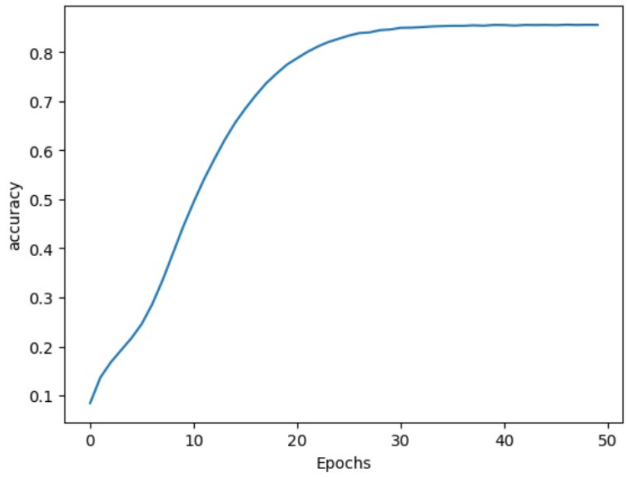
In [11]:
```
import tensorflow as tf
xs, labels = input_sequences[:,:-1],input_sequences[:,-1]
ys = tf.keras.utils.to_categorical(labels, num_classes=total_words)
```

Wir werden hier bidirektionales LSTM verwenden, das Sequenzen in beide Richtungen lernt. Eine Einbettungsebene wird hinzugefügt, um Eingabewörter in dichte Vektoren abzubilden. Diese Schicht ist sehr wichtig, da sie es dem Netzwerk ermöglicht, mehr über die Beziehung zwischen Eingaben zu erfahren und die Daten effizienter zu verarbeiten. Jedes Wort in unserem Modell hat einen Einbettungsvektor der Größe 100.

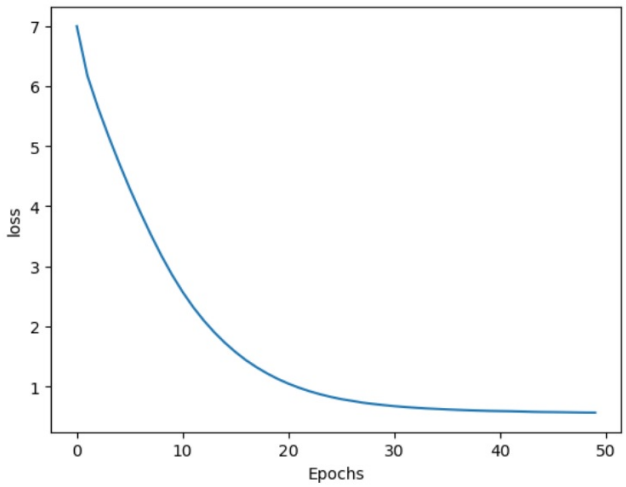
Um die Trainingsleistung des Modells zu überprüfen, zeichnen wir Genauigkeits- und Verlustwerte auf und prüfen, ob das Modell eine gute Lernleistung aufweist. Werfen Sie einen Blick auf Trainingsgenauigkeit und -verlust

In [30]:
```
# we will use here bidirectional LSTM, which learn sequences in both directions.
# An embedding layer is added to map input words into dense vectors. this layer is very important since
# it allows the network to learn more about the relationship between inputs and to process the data more efficiently.
# each word in our model will have an embedding vector of size 100.
from tensorflow.keras.optimizers import Adam
model = Sequential()
model.add(Embedding(total_words, 100, input_length=max_sequence_len-1))
model.add(Bidirectional(LSTM(150)))
model.add(Dense(total_words, activation='softmax'))
adam = Adam(lr=0.01)
model.compile(loss='categorical_crossentropy', optimizer=adam, metrics=['accuracy'])
history = model.fit(xs, ys, epochs=50, verbose=1)
#print model.summary()
print(model)
```

In [ ]:
```
# plotting model accuracy and loss
import matplotlib.pyplot as plt
def plot_graphs(history, string):
    plt.plot(history.history[string])
    plt.xlabel("Epochs")
    plt.ylabel(string)
    plt.show()
plot_graphs(history, 'accuracy')
```



In [41]:
```
plot_graphs(history, 'loss')
```



Wir können das Modell speichern und jederzeit zur Vorhersage von Wörtern verwenden:

In [2]:
```
from keras.models import load_model
!mkdir -p saved_model
model.save('saved_model/my_model_twitter')
#del model  # deletes the existing model

# relaod the saved model
saved_model2 = load_model('saved_model/my_model_twitter')
#new_model.evaluate(test_images, test_labels, verbose=2)# to evaluate the model with new data
```

Um das nächste Wort eines Textes vorherzusagen, müssen wir es zunächst tokenisieren und in eine aufgefüllte Sequenz umwandeln. Jetzt werden wir unser Modell anhand neuer Daten testen und sehen, wie gut das Modell das nächste Wort basierend auf einem Starttext vorschlagen kann.

In [35]:
```
#Predicting next word of title
tokenizer = Tokenizer(oov_token='<oov>')
tokenizer.fit_on_texts(text)
seed_text = "it seem like"
seed_text_2= "we've decided"
num_words = 2

for _ in range(num_words):
    token_list = tokenizer.texts_to_sequences([seed_text])[0]
    token_list = pad_sequences([token_list], maxlen=max_sequence_len-1, padding='pre')
    predicted = saved_model2.predict(token_list, verbose=0)
    class_x =np.argmax(predicted,axis=1)
    output_word = ""
    for word, index in tokenizer.word_index.items():
        if index == class_x:
            output_word = word
            break
    seed_text += " " + output_word
print(seed_text)
```

```
it seem like bat can
```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    "from keras.models import Sequential, load_model\n",
    "from keras.layers.core import Dense, Activation\n",
    "from keras.layers import LSTM\n",
    "\n",
    "\n",
    "from tensorflow.keras.layers import Embedding, LSTM, Dense, Bidirectional, Dropout\n",
    "from keras.optimizers import RMSprop\n",
    "from tensorflow.keras.preprocessing.text import Tokenizer\n",
    "\n",
    "\n",
    "#path ='text.txt'\n",
    "path = 'en_US.twitter.txt'\n",
    "# read and convert from one block text into a list of lines \n",
    "with open(path, encoding='utf-8') as f:\n",
    "     lines = [line.rstrip('\\n') for line in f]\n",
    "#data = open(path, encoding='utf-8').read().lower()\n",
    "#text = pd.read_csv('medium_data.csv')\n",
    "#data# = data[:1000000]\n",
    "\n",
    "#text['title'] = text['title'].apply(lambda x: x.replace(u'\\xa0',u' '))\n",
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       " \"When you meet someone special... you'll know. Your heart will beat more rapidly and you'll smile for no reason.\",\n",
       " \"they've decided its more fun if I don't.\",\n",
       " 'So Tired D; Played Lazer Tag & Ran A LOT D; Ughh Going To Sleep Like In 5 Minutes ;)',\n",
       " 'Words from a complete stranger! Made my birthday even better :)']"
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    "tokenizer.fit_on_texts(text)\n",
    "total_words = len(tokenizer.word_index) + 1\n",
    "input_sequences = []\n",
    "for line in text:\n",
    "    token_list = tokenizer.texts_to_sequences([line])[0]  \n",
    "    for i in range(1, len(token_list)):\n",
    "        n_gram_sequence = token_list[:i+1]\n",
    "        input_sequences.append(n_gram_sequence)\n",
    "\n",
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    "xs, labels = input_sequences[:,:-1],input_sequences[:,-1]\n",
    "ys = tf.keras.utils.to_categorical(labels, num_classes=total_words)"
   ]
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     ]
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      "1826/1826 [==============================] - 188s 103ms/step - loss: 6.6876 - accuracy: 0.0637\n",
      "Epoch 3/50\n",
      "1826/1826 [==============================] - 194s 106ms/step - loss: 6.2560 - accuracy: 0.0847\n",
      "Epoch 4/50\n",
      "1826/1826 [==============================] - 201s 110ms/step - loss: 5.8215 - accuracy: 0.1013\n",
      "Epoch 5/50\n",
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      "Epoch 12/50\n",
      "1826/1826 [==============================] - 189s 104ms/step - loss: 2.6866 - accuracy: 0.4635\n",
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      "1826/1826 [==============================] - 191s 104ms/step - loss: 2.4310 - accuracy: 0.5111\n",
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```

```
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      "Epoch 19/50\n",
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      "Epoch 42/50\n",
      "1826/1826 [==============================] - 189s 104ms/step - loss: 0.3989 - accuracy: 0.9067\n",
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      "1826/1826 [==============================] - 194s 107ms/step - loss: 0.3861 - accuracy: 0.9085\n",
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      "Epoch 46/50\n",
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     ]
    }
   ],
   "source": [
    "# we will use here bidirectional LSTM, which learn sequences in both directions.\n",
    "# An embedding layer is added to map input words into dense vectors. this layer is very important since\n",
    "# it allows the network to learn more about the relationship between inputs and to process the data more efficiently.\n
    "# each word in our model will have an embedding vector of size 100. \n",
    "from tensorflow.keras.optimizers import Adam\n",
    "model = Sequential()\n",
    "model.add(Embedding(total_words, 100, input_length=max_sequence_len-1))\n",
    "model.add(Bidirectional(LSTM(150)))\n",
    "model.add(Dense(total_words, activation='softmax'))\n",
    "adam = Adam(lr=0.01)\n",
    "model.compile(loss='categorical_crossentropy', optimizer=adam, metrics=['accuracy'])\n",
    "history = model.fit(xs, ys, epochs=50, verbose=1)\n",
    "#print model.summary()\n",
    "print(model)"
   ]
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    "import matplotlib.pyplot as plt\n",
    "def plot_graphs(history, string):\n",
    "    plt.plot(history.history[string])\n",
```

```
    "    plt.xlabel(\"Epochs\")\n",
    "    plt.ylabel(string)\n",
    "    plt.show()\n",
    "plot_graphs(history, 'accuracy')   "
   ]
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    "!mkdir -p saved_model    \n",
    "model.save('saved_model/my_model_twitter')  \n",
    "#del model  # deletes the existing model\n",
    "    \n",
    "# relaod the saved model \n",
    "saved_model2 = load_model('saved_model/my_model_twitter')\n",
    "#new_model.evaluate(test_images, test_labels, verbose=2)# to evaluate the model with new data "
   ]
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      "it seem like bat can\n"
     ]
    }
   ],
   "source": [
    "#Predicting next word of title\n",
    "tokenizer = Tokenizer(oov_token='<oov>') \n",
    "tokenizer.fit_on_texts(text)\n",
    "seed_text = \"it seem like\"\n",
    "seed_text_2= \"we've decided\"\n",
    "num_words = 2\n",
    "  \n",
    "for _ in range(num_words):\n",
    "    token_list = tokenizer.texts_to_sequences([seed_text])[0]\n",
    "    token_list = pad_sequences([token_list], maxlen=max_sequence_len-1, padding='pre')\n",
    "    predicted = saved_model2.predict(token_list, verbose=0)\n",
    "    class_x =np.argmax(predicted,axis=1)\n",
    "    output_word = \"\"\n",
    "    for word, index in tokenizer.word_index.items():\n",
    "        if index == class_x:\n",
    "            output_word = word\n",
    "            break\n",
    "    seed_text += \" \" + output_word\n",
    "print(seed_text)"
   ]
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      ]
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    }
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      "\u001b[1;31mKeyError\u001b[0m                                  Traceback (most recent call last)",
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```

```
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   },
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     "version": 3
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Chatbots

Die Weiterentwicklung der KI-Technologie hat vielen Branchen, einschließlich der Wirtschaft, viele Vorteile gebracht, indem sie von traditionellen zu digitalen Plattformen für Transaktionen und Kommunikation mit Kunden übergegangen ist. Chatbots sind eine vielseitige KI-Technologie. Einige Beispiele für Chatbot-Technologie sind virtuelle Assistenten wie Amazons Alexa und Google Assistant sowie Messaging-Apps wie WeChat und Facebooks Messenger.

Eine Definition von Chatbot ist, dass es sich um eine Softwareanwendung oder ein Computerprogramm handelt, das in der Lage ist, ein Gespräch mit einem Benutzer in natürlicher Sprache zu führen, die Bedeutung und den Kontext seiner Eingaben zu verstehen und entsprechend zu antworten. Das Hauptziel dieser interessanten Technologie besteht darin, das Verhalten eines Menschen als Gesprächspartner zu simulieren. Chatbot-Systeme befinden sich noch in der Entwicklung und müssen daher kontinuierlich optimiert und getestet werden.

Chatbot kann mithilfe von drei Technologien implementiert werden:

1. Künstliches neuronales Netzwerk hier
2. Wörterbeutel
3. Lemmatisierung

Bevor wir uns mit der Erstellung von Chatbots in Python befassen, müssen wir diese Begriffe im Detail verstehen.

Wörterbeutel:

Das Bag-of-Words-Modell ist eine beliebte Darstellungsmethode in natürlicher Sprache, die einen Korpus durch eine Reihe seiner Wörter mit ihren Häufigkeiten im Text symbolisiert. Dieses Modell berücksichtigt nicht die Grammatik oder die Position der Wörter, sondern nur ihr Vorkommen. Das Bag-of-Words-Modell wird zur Klassifizierung von Dokumenten verwendet, wobei die Worthäufigkeit ein Trainingsmerkmal des Klassifikators ist.

Lemmatisierung:

Lemmatisierung ist ein algorithmischer Prozess, um Wörter im Text in ihre Lemma- oder Wörterbuchform zurückzuführen. Mit anderen Worten: Es identifiziert die Bedeutung des Wortes in der Sprache und den Gesamtkontext, während es sich nicht darum kümmert, den grammatikalischen Zustand der Wörter zu erkennen. Beispielsweise wird das Wort „went" durch Lemmatisierung in das Wort „go" umgewandelt.

Anwendungsfälle

Chatbots werden in Dialogsystemen zu unterschiedlichen Zwecken eingesetzt, unter anderem zur Kundenbetreuung, zur Weiterleitung von Anfragen oder zur Informationsbeschaffung. Einige Chatbot-Anwendungen verwenden umfangreiche Wortklassifikatoren und Prozessoren für natürliche Sprache, während andere Anwendungen einfach nach allgemeinen Schlüsselwörtern im Text suchen und Antworten mithilfe von Phrasen generieren, die aus einer zugehörigen Bibliothek stammen.

Chatbots Übung

Wir werden hier Intents-JSON-Daten verwenden hier, um einen einfachen Chatbot zu erstellen. In diesem Chatbot trainieren wir das neuronale Netzwerk Artificail, um die Beziehung zwischen Wortsequenzen und ihren Tags zu lernen, da der Datensatz Tags für jeden Dateneintrag enthält. Bei diesem Ansatz generieren wir die Antwort nicht, indem wir den Kontext des Eingabetexts verstehen, sondern indem wir das ANN-Mo-

dell dazu bringen, das Tag des Eingabetexts vorherzusagen. Nachdem das Tag der Eingabedaten vorhergesagt wurde, kann aus den jedem Tag beigefügten Beispielantworten eine Antwort ausgewählt werden.

In [13]:
```
import json
import random
import string
import nltk
import numpy as np

#reading json file
file= open('intents.json').read()

chats = json.loads(file)

len(chats['intents'])
chats
```

```
    'responses': ['Happy to help!', 'Any time!', 'My pleasure'],
    'context': ['']},
   {'tag': 'noanswer',
    'patterns': [],
    'responses': ["Sorry, can't understand you",
     'Please give me more info',
     'Not sure I understand'],
    'context': ['']},
   {'tag': 'options',
    'patterns': ['How you could help me?',
     'What help you provide?',
     'How you can be helpful?'],
    'responses': ['I can guide you through Adverse management problems, order tracking, person to be contacted and Department
related queries',
     'I can provide support related to following problems technical query,management related query,order related query,trackin
g related query,procurement query,outsourcing problem,manufacturing delay,'],
    'context': ['']},
```

Der erste Schritt hier besteht darin, dass wir die Chat-Skripte mit nltk.word_tokenize kodieren. Einige Daten müssen bereinigt werden, um Tags und Satzzeichen zu entfernen, da sie dem Formular keine nützlichen Informationen liefern können.

In [2]:
```
# identifying features and target.
# tokenizing words is achieved  using nltk.word_tokenize.
# data_X represents features and data_Y represents tags of the patterns.
#  words list contains all tokens , classes contains the corresponding tags, both are sorted und duplicate-cleaned.
#The first step here is to prepare our input data by identifying features represented by chats
# and goals represented by tags. Additionally, we need to tokenize the chat texts with nltk.word_tokenize.
#Some data cleansing is required to remove the tags and punctuation as these cannot provide meaningful information
#to the model.
nltk.download('punkt')
from nltk.stem.lancaster import LancasterStemmer
stemmer = LancasterStemmer()
ignore = ['?']
words =[]
classes = []
docs = []
data_Y =[]

for chat in chats['intents']:
    for patt in chat['patterns']:
        tokens = nltk.word_tokenize(patt)#tokenize the pattern
        words.extend(tokens)##add tokens to words list
        docs.append((tokens, chat['tag'])) ## append the pattern to
        data_Y.append(chat['tag'])

    #add tags to classes list
        if chat['tag'] not in classes:
            classes.append(chat['tag'])
```

Das Entstammen von Wörtern ist ein wichtiger Schritt bei der Ableitung von Wortstämmen und deren Umwandlung in Kleinbuchstaben, da sie dem Modell dabei helfen können, das Wort auch dann zu erkennen, wenn es in unterschiedlichen Konjugationen vorkommt.

In [17]:
```
#stemming all wordsand convert them to lower cases, remove punctuations
import nltk
nltk.download('punkt')
from nltk.stem.lancaster import LancasterStemmer
#from nltk.stem import WordNetLemmatizer
stemmer =  LancasterStemmer()
words = [stemmer.stem(w.lower()) for w in words if w not in ignore]
words = sorted(list(set(words)))

# remove duplicate classes
classes = sorted(list(set(classes)))

print (len(docs), "documents")
print (len(classes), "classes", classes)
print (len(words), "unique stemmed words", words)
```

```
121 documents
43 classes ['HR_related_problem', 'Location', 'Weather', 'about', 'appointment status', 'cabin', 'check_leave', 'commission',
'competitors_in_market', 'configuration', 'connect_people', 'cost_lowering', 'customer_satisfaction', 'domain', 'email_id', 'fa
ctors_impacting_sale', 'forgot_password', 'gadgets', 'goodbye', 'greeting', 'highest_grossing', 'hours', 'invalid', 'key_custom
ers', 'leave', 'maintainence', 'manufacturing_problems', 'missing_id', 'name', 'noans', 'options', 'order_components', 'order_t
racking', 'predict_delay', 'predict_performance', 'project_handling_queries', 'search_department', 'search_person_by_id', 'solv
```

Um das ANN-Modell zu trainieren, müssen wir unsere Eingabedaten einrichten, indem wir Merkmale und Ziele definieren, die durch Muster bzw. Tags dargestellt werden. Um Eingabetext in Ganzzahlen umzuwandeln, erstellen wir aus dem Datensatz ein Bag-of-Words-Modell. Ein Vokabular ist eine Textdarstellung, die das Vorkommen von Wörtern in einem Dokument beschreibt.

```
training = []
#output = []
# create an empty array for output
output_empty = [0] * len(classes)

# create training set, bag of words for each sentence
for doc in docs:
    # initialize bag of words
    bag = []
    # list of tokenized words for the pattern
    pattern_words = doc[0]
    # stemming each word
    pattern_words = [stemmer.stem(word.lower()) for word in pattern_words]
    # create bag of words array
    for w in words:
        bag.append(1) if w in pattern_words else bag.append(0)

    # output is '1' for current tag and '0' for rest of other tags
    output_row = list(output_empty)
    output_row[classes.index(doc[1])] = 1

    training.append([bag, output_row])
print(len(classes))
# shuffling features and turning it into np.array
random.shuffle(training)
training = np.array(training)

# creating training lists
train_x = list(training[:,0])
train_y = list(training[:,1])
```

```
43
```

Wir werden ein sequentielles Modell von Keras erstellen. Die Eingabe in dieses Netzwerk ist das Array train_X . Das Modell besteht aus drei Schichten, wobei die erste Schicht 128 Neuronen, die zweite Schicht 64 Neuronen und die letzte Schicht die gleiche Anzahl Neuronen wie Klassen aufweist. Um die richtigen Gewichte zu erreichen, wird der Adam-Optimierer verwendet. Die Verlustfunktion ist eine kategoriale Kreuzentropiefunktion, da wir ein KNN-Klassifizierungsmodell trainieren.

In [5]:
```
#building neural network model,we'll create Keras' Sequential model.
#The input to this network will be the array train_X
# the model has 3 layers with the first having 128 neurons, the second having 64 neurons, and the last layer having the same numb
# Next, to reach the correct weights, Adam optimizer is used. loss function is  categorical cross-entropy function.
# And, the metric  to evaluate the model is 'accuracy'.
import tensorflow as tf
from tensorflow.keras import Sequential
from tensorflow.keras.layers import Dense, Dropout
model = Sequential()
# the number of units(neurons) could affect the resulted training accuracy
model.add(Dense(128, input_shape =(len(train_x[0]),), activation ='relu'))#input layer
model.add(Dropout(0.5))#dropout layer
model.add(Dense(64, activation ='relu'))#hidden layer
model.add(Dropout(0.5))
# output layer, classification model(activation function: softmax)
model.add(Dense(len(train_y[0]), activation ='softmax'))
adam =tf.keras.optimizers.Adam(learning_rate=0.01)
model.compile(loss= 'categorical_crossentropy',
              optimizer =adam,
              metrics=['accuracy'])
print(model.summary)
model.fit(x=train_x, y=train_y, epochs=1000, batch_size=128)
```

```
Epoch 985/1000
1/1 [==============================] - 0s 0s/step - loss: 0.1326 - accuracy: 0.9917
Epoch 986/1000
1/1 [==============================] - 0s 3ms/step - loss: 0.0611 - accuracy: 0.9669
Epoch 987/1000
1/1 [==============================] - 0s 8ms/step - loss: 0.0817 - accuracy: 0.9587
Epoch 988/1000
```

Es ist Zeit, unser Modell zu bewerten. Wir beginnen mit der Vorbereitung Ihrer Eingabedaten. Dazu gehört die Wort-Tokenisierung und die Erstellung des Bag_of_words-Modells:

In [17]:
```
# model evaluation with unknown data
# chat preparation functions
def sent_clean(sent):
    # tokenizing the pattern
    tokens = nltk.word_tokenize(sent)
    # stemming each word
    sent_words = [stemmer.stem(word.lower()) for word in tokens]
    return sent_words

# returning bag of words of the pattern
def bw(sent, words):
    # tokenizing the pattern
    sent_words = sent_clean(sent)
    # create bag of words
    bag = [0]*len(words)
    for s in sent_words:
        for i,w in enumerate(words):
            if w == s:
                bag[i] = 1


    return(np.array(bag))
```

In [18]:
```
# classify the pattern with a tag, and generate the appropriate response
error_threshold = 0.30
def classify(sent):
    # predict class probabilities from the model
    #tag_prob = model.predict(np.array([bw(sent, words)]))[0]# for sequential model
    tag_prob = model.predict([bw(sent, words)])[0] # for dnn model
    # filter out predictions below a threshold
    results = [[i,r] for i,r in enumerate(tag_prob) if r > error_threshold]
    # sort probabilities in descending order
    results.sort(key=lambda x: x[1], reverse=True)
    return_list = []
    for r in results:
        return_list.append((classes[r[0]], r[1]))# get the tag of index r[0] und prob_value is r[1]
    # return tuple of intent and probability
    return return_list

def response(sentence):
    results = classify(sentence)
    # if we have a classification then find the matching intent tag
    if results:
        # loop as long as there are matches to process
        while results:
            for chat in chats['intents']:
                # find a tag matching the first result (highst probability)
                if chat['tag'] == results[0][0]:
                    # print out a random response of the corresponding tag
                    return print(random.choice(chat['responses']))

            results.pop(0)
```

In [19]:
```
print('enter 0 if you dont want to chat with this Chatbot')
while True:

    message = input('')
    if message==0:
        break
    res = response(message)
    print(res)
```

```
enter 0 if you dont want to chat with this Chatbot
hi
Good to see you again
None
where is my order?
Please enter with order ID
None
123
please elaborate your question
None
I want to know the various departments in this company
The department are:Projects,IT,Production,OutSource
None
```


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       "    'Is anyone there?',\n",
       "    'Hey',\n",
       "    'Hola',\n",
       "    'Hello',\n",
       "    'Good day'],\n",
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       "    'Good to see you again',\n",
       "    'Hi there, how can I help?'],\n",
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       "   'patterns': ['Bye',\n",
       "    'See you later',\n",
       "    'Goodbye',\n",
       "    'Nice chatting to you, bye',\n",
       "    'Till next time'],\n",
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       "   'context': ['']},\n",
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       "   'patterns': ['Thanks',\n",
       "    'Thank you',\n",
       "    \"That's helpful\",\n",
       "    'Awesome, thanks',\n",
       "    'Thanks for helping me'],\n",
       "   'responses': ['Happy to help!', 'Any time!', 'My pleasure'],\n",
       "   'context': ['']},\n",
       "  {'tag': 'noanswer',\n",
       "   'patterns': [],\n",
       "   'responses': [\"Sorry, can't understand you\",\n",
       "    'Please give me more info',\n",
       "    'Not sure I understand'],\n",
       "   'context': ['']},\n",
       "  {'tag': 'options',\n",
       "   'patterns': ['How you could help me?',\n",
       "    'What help you provide?',\n",
       "```
```

```
        "    'How you can be helpful?'],\n",
        "   'responses': ['I can guide you through Adverse management problems, order tracking, person to be contacted and D
        "    'I can provide support related to following problems technical query,management related query,order related que
        "   'context': ['']},\n",
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        "   'patterns': ['where is order with id 431B67?',\n",
        "    'track order 562B78',\n",
        "    'Where is my order with id 561A24?'],\n",
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        "   'patterns': ['where is the order',\n",
        "    'where is my order',\n",
        "    'locate the order',\n",
        "    'Delivery date of order'],\n",
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        "    'What is the Location of order 23A31?'],\n",
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        "    'It is in Berlin',\n",
        "    'It has reached china',\n",
        "    'It has reached Banglore'],\n",
        "   'context': ['']},\n",
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        "    'set an appointment with Sujata Nandi'],\n",
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        "   'context': ['']},\n",
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        "   'responses': ['No Not On Leave', 'Yes On Leave'],\n",
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        "    'what changes could lower cost?'],\n",
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        "   'context': ['']},\n",
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        "   'patterns': ['I forgot my Login password?',\n",
        "    'what to do when someone forgets Login password?',\n",
        "    'I forgot my Laptop password',\n",
        "    'Forgot Wifi password'],\n",
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        "   'patterns': ['abx@gmail.com', 'abc@kiit.ac.in'],\n",
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        "   'context': ['']},\n",
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        "    'Miscommunication Conflicts needs to be resolved',\n",
        "    'Risk Management issue has occured',\n",
        "    'skilled employees needed urgently'],\n",
        "   'responses': ['Please contact the project depatment'],\n",
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```

```
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"   'patterns': ['problem related to Job design and analysis',\n",
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"    'Training and development issues are to be handled',\n",
"    'Compensation and benefits of the working employee',\n",
"    'Legal issues of department like accidents in the company'],\n",
"   'responses': ['Please Contact the HR team for this problem.'],\n",
"   'context': ['']},\n",
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"   'patterns': ['Impact on sale?', 'factors impacting sale this year?'],\n",
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"    'this year our sale might increase during durga puja',\n",
"    'this year sale might be impacted due to demonitisation'],\n",
"   'context': ['']},\n",
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"   'patterns': ['how have we improved our sale from last year?',\n",
"    'what is the profit this year?'],\n",
"   'responses': ['we have improved our sale by increasing our customers upto 2 lakh',\n",
"    'profit earned is 15%'],\n",
"   'context': ['']},\n",
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"    'Is the customer happy?',\n",
"    'what was the customer feedback?'],\n",
"   'responses': ['Customer was happy and has given good rating'],\n",
"   'context': ['']},\n",
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"   'patterns': ['what are the gadgets in stock?', 'which products we have?'],\n",
"   'responses': ['hardisk,pendrives, wireless bluetooth,Laptops,Gaming Accessories'],\n",
"   'context': ['']},\n",
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"   'patterns': ['what is the Commission rate?',\n",
"    'Commission rate on each product?'],\n",
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"   'context': ['']},\n",
"  {'tag': 'invalid',\n",
"   'patterns': ['Marry me',\n",
"    'I love You',\n",
"    'date me',\n",
"    'chat with me',\n",
"    'I am bored'],\n",
"   'responses': ['Please ask organisation related query.'],\n",
"   'context': ['']},\n",
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"   'patterns': ['why', 'how', 'when', 'I', 'you'],\n",
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"    'Delay is due to inavailable components'],\n",
"   'context': ['']},\n",
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"   'patterns': ['what is your name?', 'what should I call you?'],\n",
"   'responses': [\"I'm Bruno\", \"Hey!I'm Bruno\"],\n",
"   'context': ['']},\n",
"  {'tag': 'about',\n",
"   'patterns': ['how you doing?', 'how are you'],\n",
"   'responses': ['Thanks For Asking!How can I help you?'],\n",
"   'context': ['']},\n",
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"    'How to configure my computer',\n",
"    'software configuration of computer',\n",
"    'steps to configure computer',\n",
"    'How to configure my desktop',\n",
"    'software configuration of desktop',\n",
"    'steps to configure desktop'],\n",
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"   'responses': [\"It's 36C according to accuweather\"],\n",
"   'context': ['']},\n",
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"   'patterns': ['Is Michel Sharma on leave?',\n",
"    'Is Siddhart Roy present today?',\n",
"    'Is Shantanu Bhatt in office?'],\n",
"   'responses': [\"Give me a moment!I'll just check\", 'yes', 'no'],\n",
"   'context': ['']},\n",
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"   'patterns': ['Opening hours of the cafeteria?',\n",
"    'when does the cafeteria open',\n",
"    'office canteen opening time'],\n",
"   'responses': ['It is open from Monday-Saturday 9:00am-7:30pm'],\n",
"   'context': ['']},\n",
"  {'tag': 'cabin',\n",
```

```
        "   'patterns': ['where is VP cabin?',\n",
        "    'Where is Head IT cabin?',\n",
        "    'Where is AI department',\n",
        "    'Where is Project head department?',\n",
        "    'where is cafeteria',\n",
        "    'guide me to the canteen'],\n",
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        "    'Block-B 2nd Floor',\n",
        "    'Block-D Ground Floor'],\n",
        "   'context': ['']},\n",
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        "   'patterns': ['How to improve team members domain knowledge',\n",
        "    'improving domain knowledge of team members'],\n",
        "   'responses': ['set up key meetings and workshop,create a shared drive for information,Hold informal sharing sess
        "   'context': ['']}]}"
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     "import random\n",
     "import string\n",
     "import nltk \n",
     "import numpy as np\n",
     "\n",
     "#reading json file\n",
     "file= open('intents.json').read()\n",
     "\n",
     "chats = json.loads(file)\n",
     "\n",
     "len(chats['intents'])\n",
     "chats\n",
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       "[nltk_data]   Package punkt is already up-to-date!\n"
      ]
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     "# identifying features and target.\n",
     "# tokenizing words is achieved  using nltk.word_tokenize.\n",
     "# data_X represents features and data_Y represents tags of the patterns.\n",
     "#  words list contains all tokens , classes contains the corresponding tags, both are sorted und duplicate-cleaned.\n
     "#The first step here is to prepare our input data by identifying features represented by chats\n",
     "# and goals represented by tags. Additionally, we need to tokenize the chat texts with nltk.word_tokenize. \n",
     "#Some data cleansing is required to remove the tags and punctuation as these cannot provide meaningful information\n",
     "#to the model.\n",
     "nltk.download('punkt')\n",
     "from nltk.stem.lancaster import LancasterStemmer\n",
     "stemmer = LancasterStemmer()\n",
     "ignore = ['?']\n",
     "words =[]\n",
     "classes = []\n",
     "docs = []\n",
     "data_Y =[]\n",
     "\n",
     "for chat in chats['intents']:\n",
     "    for patt in chat['patterns']:\n",
     "        tokens = nltk.word_tokenize(patt)#tokenize the pattern\n",
     "        words.extend(tokens)##add tokens to words list\n",
     "        docs.append((tokens, chat['tag'])) ## append the pattern to\n",
     "        data_Y.append(chat['tag'])\n",
     "        \n",
     "    #add tags to classes list\n",
     "        if chat['tag'] not in classes:\n",
     "            classes.append(chat['tag'])"
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       "226 unique stemmed words [\"'s\", ',', '.', '23a12', '23a31', '32712', '345a23', '431b67', '561a24', '562b78', '@',
      ]
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```

```
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      "[nltk_data]   Package punkt is already up-to-date!\n"
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    "nltk.download('punkt')\n",
    "from nltk.stem.lancaster import LancasterStemmer\n",
    "stemmer = LancasterStemmer()\n",
    "words = [stemmer.stem(w.lower()) for w in words if w not in ignore]\n",
    "words = sorted(list(set(words)))\n",
    "\n",
    "# remove duplicate classes\n",
    "classes = sorted(list(set(classes)))\n",
    "\n",
    "print (len(docs), \"documents\")\n",
    "print (len(classes), \"classes\", classes)\n",
    "print (len(words), \"unique stemmed words\", words)"
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    "# bag-of-words is used to convert words into numbers. \n",
    "#  words and classes act as a vocabulary for patterns and tags respectively.\n",
    "# We?ll use words and classes to create two arrays, of the same lengths as the sizes of two vocabulary lists, for every\n",
    "# The array will have values 1 if the word is present in the patterns/tag of the chat, otherwise 0. \n",
    "\n",
    "training = []\n",
    "#output = []\n",
    "# create an empty array for output\n",
    "output_empty = [0] * len(classes)\n",
    "\n",
    "# create training set, bag of words for each sentence\n",
    "for doc in docs:\n",
    "    # initialize bag of words\n",
    "    bag = []\n",
    "    # list of tokenized words for the pattern\n",
    "    pattern_words = doc[0]\n",
    "    # stemming each word\n",
    "    pattern_words = [stemmer.stem(word.lower()) for word in pattern_words]\n",
    "    # create bag of words array\n",
    "    for w in words:\n",
    "        bag.append(1) if w in pattern_words else bag.append(0)\n",
    "\n",
    "    # output is '1' for current tag and '0' for rest of other tags\n",
    "    output_row = list(output_empty)\n",
    "    output_row[classes.index(doc[1])] = 1\n",
    "\n",
    "    training.append([bag, output_row])\n",
    "print(len(classes))\n",
    "# shuffling features and turning it into np.array\n",
    "random.shuffle(training)\n",
    "training = np.array(training, dtype=object)\n",
    "# creating training lists\n",
    "train_x = list(training[:,0])\n",
    "train_y = list(training[:,1])  "
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    "len(words)"
   ]
```

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      "Epoch 2/1000\n",
      "1/1 [==============================] - 0s 16ms/step - loss: 3.6834 - accuracy: 0.0992\n",
      "Epoch 3/1000\n",
      "1/1 [==============================] - 0s 18ms/step - loss: 3.6309 - accuracy: 0.0992\n",
      "Epoch 4/1000\n",
      "1/1 [==============================] - 0s 9ms/step - loss: 3.5270 - accuracy: 0.1488\n",
      "Epoch 5/1000\n",
      "1/1 [==============================] - 0s 7ms/step - loss: 3.3417 - accuracy: 0.1901\n",
      "Epoch 6/1000\n",
      "1/1 [==============================] - 0s 9ms/step - loss: 3.2504 - accuracy: 0.2314\n",
      "Epoch 7/1000\n",
      "1/1 [==============================] - 0s 16ms/step - loss: 3.1343 - accuracy: 0.2066\n",
      "Epoch 8/1000\n",
      "1/1 [==============================] - 0s 10ms/step - loss: 3.0527 - accuracy: 0.2727\n",
      "Epoch 9/1000\n",
      "1/1 [==============================] - 0s 8ms/step - loss: 2.8387 - accuracy: 0.2479\n",
      "Epoch 10/1000\n",
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    "#The input to this network will be the array train_X\n",
    "# the model has 3 layers with the first having 128 neurons, the second having 64 neurons, and the last layer having th
    "# Next, to reach the correct weights, Adam optimizer is used. loss function is  categorical cross-entropy function.\n"
    "# And, the metric  to evaluate the model is 'accuracy'.\n",
    "import tensorflow as tf\n",
    "from tensorflow.keras import Sequential\n",
    "from tensorflow.keras.layers import Dense, Dropout\n",
    "model = Sequential()\n",
    "# the number of units(neurons) could affect the resulted training accuracy\n",
    "model.add(Dense(128, input_shape =(len(train_x[0]),), activation ='relu'))#input layer\n",
    "model.add(Dropout(0.5))#dropout layer\n",
    "model.add(Dense(64, activation ='relu'))#hidden layer\n",
    "model.add(Dropout(0.5))\n",
    "# output layer, classification model(activation function: softmax)\n",
    "model.add(Dense(len(train_y[0]), activation ='softmax'))\n",
    "adam =tf.keras.optimizers.Adam(learning_rate=0.01)    \n",
    "model.compile(loss= 'categorical_crossentropy', \n",
    "              optimizer =adam,\n",
    "              metrics=['accuracy'])\n",
    "print(model.summary)\n",
    "model.fit(x=train_x, y=train_y, epochs=1000, batch_size=128)\n"
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    "# chat preparation functions\n",
    "def sent_clean(sent):\n",
    "    # tokenizing the pattern\n",
    "    tokens = nltk.word_tokenize(sent)\n",
    "    # stemming each word\n",
    "    sent_words = [stemmer.stem(word.lower()) for word in tokens]\n",
    "    return sent_words\n",
    "\n",
    "# returning bag of words of the pattern\n",
    "def bw(sent, words):\n",
    "    # tokenizing the pattern\n",
    "    sent_words = sent_clean(sent)\n",
    "    # create bag of words\n",
    "    bag = [0]*len(words)  \n",
    "    for s in sent_words:\n",
    "        for i,w in enumerate(words):\n",
    "            if w == s: \n",
    "                bag[i] = 1\n",
    "                \n",
    "\n",
    "    return(np.array(bag))"
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    "# classify the pattern with a tag, and generate the appropriate response\n",
    "error_threshold = 0.30\n",
    "def classify(sent):\n",
    "    # predict class probabilities from the model\n",
    "    #tag_prob = model.predict(np.array([bw(sent, words)]))[0]# for sequential model \n",
    "    tag_prob = model.predict([bw(sent, words)])[0] # for dnn model\n",
    "    # filter out predictions below a threshold\n",
    "    results = [[i,r] for i,r in enumerate(tag_prob) if r > error_threshold]\n",
    "    # sort probabilities in descending order\n",
    "    results.sort(key=lambda x: x[1], reverse=True)\n",
    "    return_list = []\n",
    "    for r in results:\n",
    "        return_list.append((classes[r[0]], r[1]))# get the tag of index r[0] und prob_value is r[1]\n",
    "    # return tuple of intent and probability\n",
    "    return return_list\n",
    "\n",
    "def response(sentence):\n",
    "    results = classify(sentence)\n",
    "    # if we have a classification then find the matching intent tag\n",
    "    if results:\n",
    "        # loop as long as there are matches to process\n",
    "        while results:\n",
    "            for chat in chats['intents']:\n",
    "                # find a tag matching the first result (highst probability)\n",
```

```
    "                if chat['tag'] == results[0][0]:\n",
    "                    # print out a random response of the corresponding tag\n",
    "                    return print(random.choice(chat['responses']))\n",
    "\n",
    "            results.pop(0)"
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    "    res = response(message)\n",
    "    print(res)\n",
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intents.json (11.79 KB)

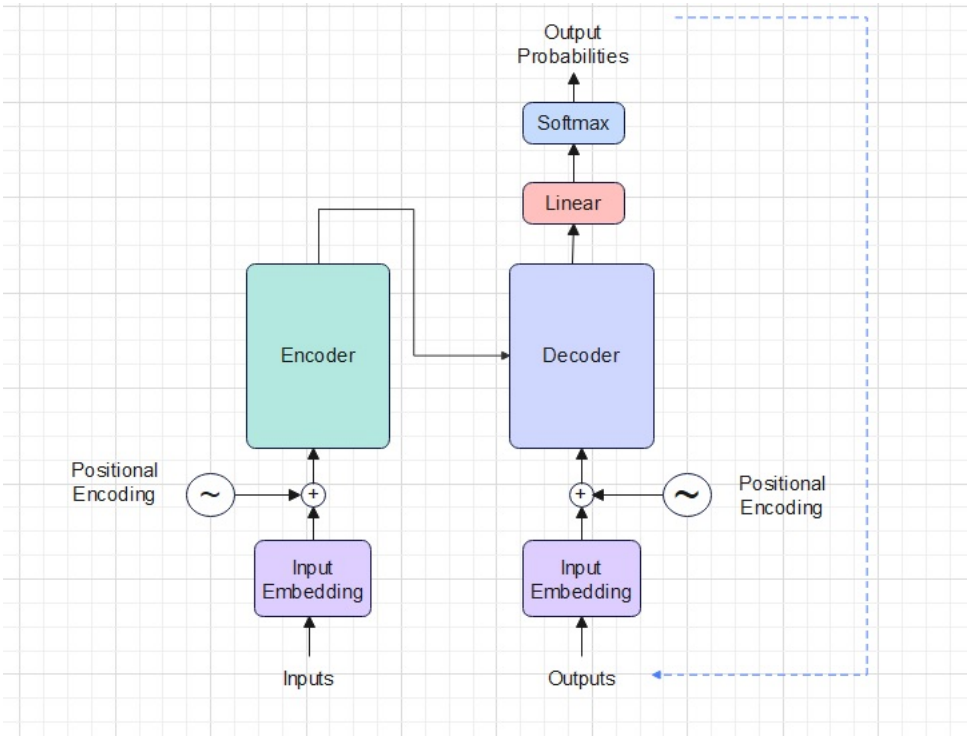
Transformers

Der Transformer im NLP ist eine neue Technologie, die darauf abzielt, Sequenz-zu-Sequenz-Probleme durch die Einbeziehung langfristiger Abhängigkeiten zu lösen. Es verwendet das Selbstaufmerksamkeitskonzept, um den Kontext der Eingabesequenz zu kodieren und einzubetten.

Beim Deep Learning ist Aufmerksamkeit ein neues Konzept, das es ermöglicht, auf Teile der Eingabesequenz zu konzentrieren, Um ein Verständnis des Kontexts als Ergebnis vermittelt zu werden. Und dies ist eine Art von Aufmerksamkeit in einem Transformatormodell namens Encoder-Decoder-Aufmerksamkeit, bei dem eine Verbindung/Korrelation zwischen Eingabe und Ausgabe abgebildet wird. Bei einer anderen Art der Aufmerksamkeit namens Selbstaufmerksamkeit erstellt das Modell ähnliche Verbindungen, jedoch innerhalb eines einzelnen Satzes, um eine Darstellung der Sequenz zu berechnen. Der dritte Typ wird als Selbstaufmerksamkeit in der Ausgabesequenz bezeichnet, wobei die Aufmerksamkeit hier nur auf die Wörter vor einem bestimmten Wort beschränkt ist, während die übrigen Wörter maskiert sind.

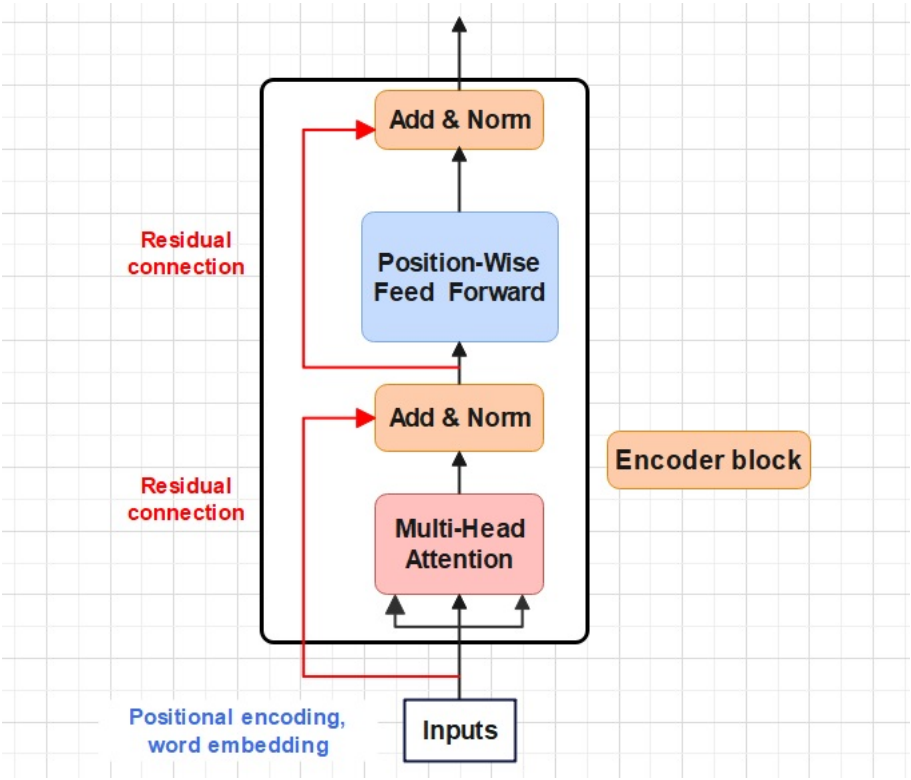
Encoder-Decoder-Transformator-Architektur:

Die folgende Abbildung zeigt einen Encoder-Decoder-Transformator. Die Aufgabe des Encoders auf der linken Seite besteht darin, eine Eingabesequenz Darstellungen zuzuordnen, die vom Decoder zusammen mit der Decoderausgabe im vorherigen Zeitschritt verwendet werden, um eine Ausgabesequenz zu generieren.



Einbettungen sind die Kernidee des Transformators für neuronale maschinelle Übersetzungsaufgaben (NMT). Durch Einbettungen kann das Modell mit mehr Informationen über die Wörter versorgt werden und das Modell kann effizienter über den Kontext lernen. Dies funktioniert, indem nach dem Einbettungsvektor für jedes in das Netzwerk eingespeiste Wort gesucht wird. Die Bedeutung der Wörter wird so kodiert, dass Wörter mit ähnlicher Bedeutung in ähnlichen Vektoren dargestellt werden.

Die Positionskodierung informiert das Netzwerk über die Positionen der Wörter oder darüber, wo sich das Wort im Satz befindet. Der Encoder verwendet diese Codierung zusammen mit den Einbettungen der Wörter, um über mehrere Encoderblöcke lineare Algebraoperationen an den Einbettungsvektoren durchzuführen, um Merkmale über die Kontexte für jedes Wort innerhalb des gesamten Satzes zu extrahieren und die Einbettungsvektoren mit diesen Merkmalen anzureichern.

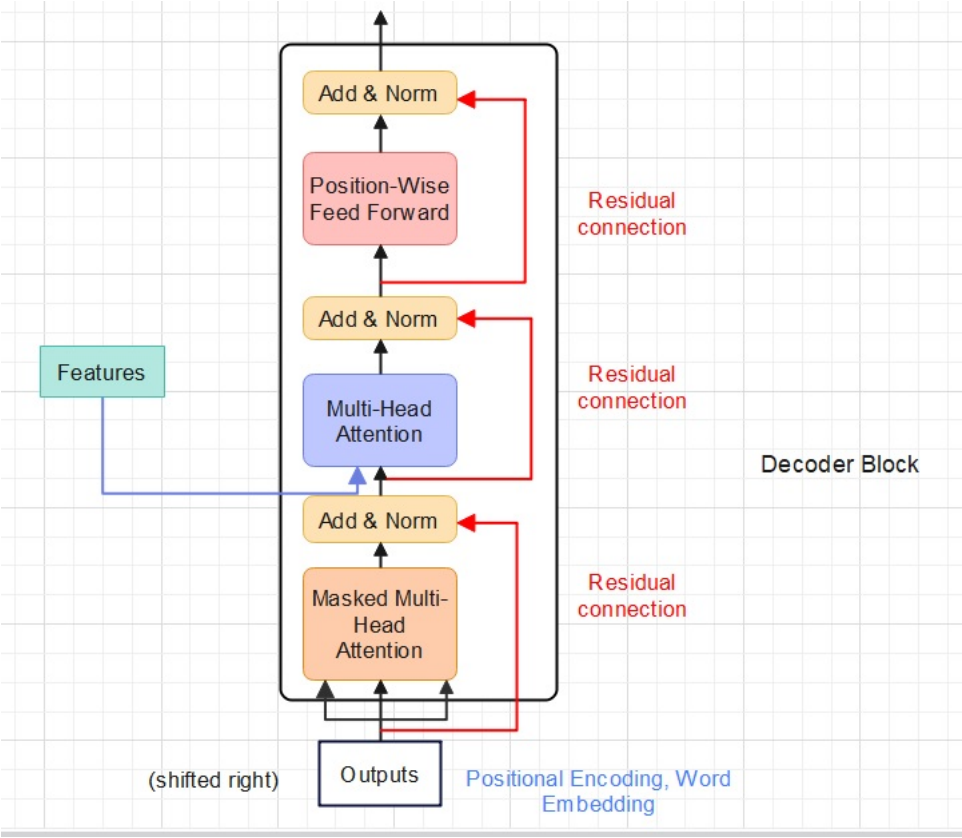


Der Encoderblock nutzt den Selbstaufmerksamkeitsmechanismus, um jeden Einbettungsvektor mit Kontextinformationen des Tokens in seinem Satz anzureichern. Da ein Wortvektor mehrere Semantiken enthalten kann, werden mehrere Köpfe verwendet, sodass jeder Kopf den Vektor mit seiner eigenen Matrix projiziert, um eine sematische Eigenschaft zu überprüfen. Beispielsweise kann das Wort „Königin" mehrere semantische Eigenschaften haben, etwa weiblich, königlich oder Macht.

Das positionsbezogene Feed-Forward-Netzwerk verfügt über zwei lineare Schichten, die zusammen mit Kontextinformationen aus der Multi-Head-Aufmerksamkeit eine Transformation auf jeden Einbettungsvektor anwenden. Die Hauptaufgabe dieses Netzwerks besteht darin, jeden Worteinbettungsvektor unabhängig mit identischen Gewichten basierend auf seiner Position in der Sequenz zu verarbeiten.

Restverbindungen sorgen dafür, dass die Token-Einbettungen und Positionsinformationen von der vorherigen Schicht zur weiteren Verarbeitung in die nachfolgende Schicht übertragen werden.

Die Schichtnormalisierung wird verwendet, um das Training zu stabilisieren, indem verhindert wird, dass sich der Mittelwert und die Standardabweichung des Einbettungsvektors verschieben. Das heißt, alle Elemente im Einbettungsvektor auf den gleichen Maßstab zu bringen, wodurch das Netzwerk schneller konvergieren und trainieren kann.



Der Decoder verwendet die vom Encoder generierten Mermale, um eine Ausgabe zu erzeugen. Die Eingabe in den Decoder ist die nach rechts verschobene Ausgabe des vorherigen Zeitschritts, die zu einer Folge von positionscodierten Einbettungen wird. Die maskierte Multi-Head-Aufmerksamkeit ist eine wichtige Ebene im Decoder, die die Eingabe mit Masken versorgt, um der nächsten Multi-Head-Aufmerksamkeitsschicht dabei zu helfen, die maskierten Positionen in den vom Encoder berechneten Merkmalen zu verbergen. Der Decoder erreicht diesen Schritt, indem er die Aufmerksamkeitswerte der maskierten Positionen auf negative Werte (-∞) setzt.

Die Multi-Head-Aufmerksamkeitsschicht, die auch als Quelle-Ziel-Aufmerksamkeit bekannt ist, berechnet anschließend Aufmerksamkeitsmerkmale zwischen Eingabeeinbettungen und der Ausgabe aus dem vorherigen Zeitschritt. Die aus dieser Schicht resultierenden Merkmalsvektoren sind für das Training erforderlich, da sie der nächsten Feed-Forward-Schicht dabei helfen, neue Gewichte des Netzwerks zu lernen.

Anschließend wendet der Decoder eine lineare Transformation auf den Ausgabevektor an, um die Größe eines Einbettungsvektors in einen Vokabulargrößenvektor zu ändern. Softmax wird hier verwendet, um den resultierenden Logit-Vector in einen Wahrscheinlichkeitsvektor mit der gleichen Größe wie das Korpusvokabular zu skalieren.

Die Ausgabe des Decoders ist jeweils ein Token. Das Ausgabetoken wird dann als nachfolgende Eingabe für den Decoder verwendet, nachdem es durch die Einbettungsschicht in einen Einbettungsvektor umgewandelt wurde.

Transformer kann für viele NLP-Aufgaben verwendet werden, einschließlich Übersetzung und Textklassifizierung.

Transformers Übung

Bevor wir mit der Verwendung von Transformatoren beginnen, müssen wir alle erforderlichen Bibliotheken installieren:

```
In [2]: # installing transformer library
        !pip install transformers datasets evaluate
```

```
Requirement already satisfied: transformers in c:\users\la2022\anaconda3\lib\site-packages (4.25.1)
Collecting datasets
  Downloading datasets-2.9.0-py3-none-any.whl (462 kB)
     ---------------------------------------- 462.8/462.8 kB 5.8 MB/s eta 0:00:00
Collecting evaluate
  Downloading evaluate-0.4.0-py3-none-any.whl (81 kB)
     ---------------------------------------- 81.4/81.4 kB 4.4 MB/s eta 0:00:00
Requirement already satisfied: filelock in c:\users\la2022\anaconda3\lib\site-packages (from transformers) (3.6.0)
Requirement already satisfied: packaging>=20.0 in c:\users\la2022\anaconda3\lib\site-packages (from transformers) (21.3)
```

In diesem Beispiel wenden wir einen Transformator für die Textklassifizierungsaufgabe im E-Commerce-Datensatz hier an. Die Datensätze bestehen aus zwei Spalten: Produktbeschreibung, die einige Merkmale und Attribute des Produkts enthält, während die zweite Spalte die Produktklasse mit vier Hauptkategorien enthält: „Elektronik", „Haushalt", „Bücher" und „Kleidung und Accessoires". Die Kategorien der Produkte müssen in Zahlenwerte umgerechnet werden.

In [22]:
```
# installing dataset
import pandas as pd
from sklearn.utils import shuffle

data = pd.read_csv("ecomm_data.csv")
# remaove na values
data = data.dropna()
# shuffle data
data = shuffle(data)
# rename column names using col index
data.rename(columns={data.columns[0]: "label", data.columns[1]: "product_description"}, inplace=True)
print(data.head(1)['product_description'])

# replace catecorical with numerical values
data['label'].replace([ "Electronics",  "Household", "Books", "Clothing & Accessories"],
                      [0, 1, 2, 3], inplace=True)
```

```
5882    Elite Home 600SSQU053DLHS6 Sheet Set, Queen Si...
Name: product_description, dtype: object
```

Der nächste Schritt umfasst die Konvertierung des Wörterbuchs in einen Datensatz, damit dieser anschließend vom Tokenizer verwendet werden kann. Nur ein Teil des Datensatzes wird für das Training des Transformators verwendet. Um die Wörter der Trainingsdaten zu tokenisieren, verwenden wir einen vorab trainierten Ditilbert-Tokenizer, um Token zu erzeugen, die dem Typ des Transformators entsprechen, in unserem Fall des Ditilbert-Transformators. Zur Tokenisierung müssen wir Eingabesequenzen auf die maximale Eingabelänge von DistilBERT kürzen.

In [24]:
```
# convert data into dataset
df = {'product_desc': data['product_description'], 'label': data['label']}
from datasets import Dataset
out_df = Dataset.from_dict(df)

print(out_df[:2])

#load a DistilBERT tokenizer, tokeniztation of the words
from transformers import AutoTokenizer
# using the distilbert tokenizer
tokenizer = AutoTokenizer.from_pretrained("distilbert-base-uncased",return_tensors='pt')

#tokenization function
# truncate sequences longer than DistilBERT's maximum input length

def tokenize(data):
    return tokenizer(data["product_desc"], truncation=True)

#splitting dataset into train and test:
train = out_df[:1000]
test =  out_df[1000:1100]
train = Dataset.from_dict(train)
test = Dataset.from_dict(test)


print(train[:2])
print(test[:2])
```

In [6]:
```
# tokenizing train and test sets using map function, to avoid creating tokenizers.Encoding objects and keep dict or Dataset
# objects with keys
train_tokens = train.map(tokenize, batched=True)
test_tokens= test.map(tokenize, batched=True)
```

```
100% 1/1 [00:00<00:00, 3.64ba/s]

100% 1/1 [00:00<00:00, 21.59ba/s]
```

Wie beim Kürzungsschritt müssen wir Padding verwenden, um Eingabestapel mit der gleichen Länge zu erzeugen. Dies wird mit DataCollatorWithPadding durchgeführt, das die empfangenen Eingaben dynamisch auffüllt.

In [7]:
```
# datacollatorwithpadding: to create batches with padding to the maximum input length; pytorch implementation..
from transformers import DataCollatorWithPadding
data_collator = DataCollatorWithPadding(tokenizer=tokenizer)
```

Als nächstes definieren wir eine Genauigkeitsfunktion, um die Vorhersageleistung des Transformators zu bewerten. Zu diesem Zweck verwenden wir eine „Genauigkeits"-Metrik, die als Verhältnis der korrekten Vorhersagen zur Gesamtzahl der Vorhersagen berechnet wird. Das Zuordnen vorhergesagter IDs zu ihren Beschriftungen ist ebenfalls ein notwendiger Schritt, der es dem Transformator ermöglicht, Vorhersagen oder Klassen als Texte statt als Zahlen auszugeben.

In [25]:
```
# defining a function to calculate prediction performance of the model:  'accuracy' metric will be used

import numpy as np
import evaluate

accuracy = evaluate.load("accuracy")
def acc_calculate(pred):
    predicted, actual = pred
    predicted = np.argmax(predicted, axis=1)# argmax returns indices of the maximum values along axis 1;
    # predicted contains the probabilities of all classes for each entry in the dataset,
    # the index 0 means that probabilty of class 0 is the highst and so on..
    return accuracy.compute(predictions=predicted, references=actual)

# create a map of the expected ids to their labels with id2label and label2id:

id2label = {0: "Electronics", 1: "Household", 2: "Books", 3:"Clothing & Accessories"}
label2id = {"Electronics": 0, "Household": 1, "Books":2, "Clothing & Accessories":3}
```

Jetzt ist es an der Zeit, unseren Transformator zu bauen und zu trainieren. Wir werden den vorab trainierten Distilbert-Transformator mithilfe des Python-Pakets AutoModelForSequenceClassification definieren, einem generischen Sequenzklassifizierungsmodell, das zum Initiieren des

Transformators mit einem vorab trainierten Modell verwendet wird. Für unser Beispiel verwenden wir die Gewichte des vorab trainierten Bert-Modells. Der Transformator wird an einem 3-Phasen-Trainingsset trainiert und anschließend mithilfe von Testtokens wie folgt bewertet:

In [10]:
```
# defining the transformer
from transformers import AutoModelForSequenceClassification, TrainingArguments, Trainer

#from_pretrained(): to load the pretrained Bert model weights
#AutoModelForSequenceClassification: is a generic sequence classification model that will be instantiated using a pretarined Bert

transformer = AutoModelForSequenceClassification.from_pretrained(
"distilbert-base-uncased", num_labels=4, id2label=id2label, label2id=label2id, from_tf=True
)
```

```
All TF 2.0 model weights were used when initializing DistilBertForSequenceClassification.

All the weights of DistilBertForSequenceClassification were initialized from the TF 2.0 model.
If your task is similar to the task the model of the checkpoint was trained on, you can already use DistilBertForSequenceClassi
fication for predictions without further training.
```

In [ ]:
```
# defining the training parameters
training_pars = TrainingArguments(
    output_dir="my_transformer",
    per_device_train_batch_size=64,
    per_device_eval_batch_size=64,
    num_train_epochs=3,
    weight_decay=0.01,
    evaluation_strategy="epoch",
    save_strategy="epoch",
    load_best_model_at_end=True)

# defining the trainer of the model
#The Trainer class provides an API for feature-complete training in PyTorch
trainer = Trainer(
    model=transformer,
    args=training_pars,
    train_dataset= train_tokens,
    eval_dataset=test_tokens,
    tokenizer=tokenizer,
    data_collator=data_collator,
    compute_metrics=acc_calculate,
)
#training the transformer
trainer.train()
```

In [27]:
```
trainer.evaluate()
```

```
The following columns in the evaluation set don't have a corresponding argument in `DistilBertForSequenceClassification.forward
` and have been ignored: product_desc. If product_desc are not expected by `DistilBertForSequenceClassification.forward`,  you
can safely ignore this message.
***** Running Evaluation *****
  Num examples = 100
  Batch size = 64
```

Out[27]:
```
{'eval_loss': 0.3000350892543793, 'eval_accuracy': 0.91}
```

Für die zukünftige Verwendung können wir den trainierten Transformator in einer Datei speichern. Um Vorhersagen für neue Dateneingaben zu treffen, können wir die Transformer-Pipeline verwenden, die eine Wrapper-Klasse anderer Pipelines ist, in unserem Fall die Textklassifizierung. Diese Pipeline wird verwendet, um Eingabetext basierend auf dem trainierten Transfromer zu klassifizieren. Das Argument „return_all_scores" ist auf „true" gesetzt, sodass wir alle Bewertungen für jedes Label einer Vorhersage erhalten. Hier ist ein Beispiel:

In [ ]:
```
#save trainer to a file
trainer.save_model("./Distilbert_based_transformer")
transformer_trained = AutoModelForSequenceClassification.from_pretrained("./Distilbert_based_transformer")
```

In [26]:
```
from transformers import TextClassificationPipeline
# This pipeline has a return_all_scores parameter on its __call__ method that allows you to get all scores for each label on a pr
pipe = TextClassificationPipeline(model=transformer_trained, tokenizer=tokenizer)
prediction = pipe("NetGen 4k Wi-Fi 16 MP Ultra HD Action Camera", return_all_scores=True)
prediction
```

```
C:\Users\la2022\anaconda3\lib\site-packages\transformers\pipelines\text_classification.py:104: UserWarning: `return_all_scores`
is now deprecated,  if want a similar funcionality use `top_k=None` instead of `return_all_scores=True` or `top_k=1` instead of
`return_all_scores=False`.
  warnings.warn(
```

Out[26]:
```
[[{'label': 'Electronics', 'score': 0.9508970975875854},
  {'label': 'Household', 'score': 0.017261911183595657},
  {'label': 'Books', 'score': 0.017655229195952415},
  {'label': 'Clothing & Accessories', 'score': 0.014185710810124874}]]
```

Jetzt werden wir das vorab trainierte GPT 2-Modell verwenden, um Texte zu generieren:

In [ ]:
```
# using GPT-2 to generate text
from transformers import pipeline
text_generator = pipeline('text-generation', model='gpt2')
# generate 5 different sentences by sampling from the top 10 hits:
#Temperature is a hyper-parameter used to control the randomness of predictions by scaling the logits before applying softmax.
# when temperature is a large value (e.g. 1), the GPT-2 model produces more diversity and also more mistakes and viseversa
```

In [ ]:
```
text_generator.save_pretrained('gpt2_pretrained')
```

In [ ]:
```
sentences = text_generator("in the last few years, a bunch of changes", do_sample=True, top_k=10, temperature=0.6, max_length=50,
for sent in sentences:
  print(sent["generated_text"])
  print("#"*50)
```

```
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    "!pip install transformers datasets evaluate"
   ]
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      "Name: product_description, dtype: object\n"
     ]
    }
   ],
   "source": [
    "# installing dataset\n",
    "import pandas as pd\n",
    "from sklearn.utils import shuffle\n",
    "from transformers import AutoModelForSequenceClassification, TrainingArguments, Trainer\n",
    "data = pd.read_csv(\"ecomm_data.csv\")\n",
    "# remaove na values\n",
    "data = data.dropna()\n",
    "# shuffle data\n",
    "data = shuffle(data)\n",
    "# rename column names using col index\n",
    "data.rename(columns={data.columns[0]: \"label\", data.columns[1]: \"product_description\"}, inplace=True)\n",
    "print(data.head(1)['product_description'])\n",
    "\n",
    "# replace catecorical with numerical values\n",
    "data['label'].replace([ \"Electronics\",  \"Household\", \"Books\", \"Clothing & Accessories\"],\n",
    "                       [0, 1, 2, 3], inplace=True)"
   ]
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   "metadata": {},
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     "name": "stdout",
     "output_type": "stream",
     "text": [
      "{'product_desc': ['TP-Link TL-UE300 USB 3.0 to RJ45 Gigabit Ethernet Network Adapter Style name:UE300   UE300 adds gi
      "{'product_desc': ['TP-Link TL-UE300 USB 3.0 to RJ45 Gigabit Ethernet Network Adapter Style name:UE300   UE300 adds gi
      "{'product_desc': ['Maybelline New York Fit Me Matte with Poreless Foundation, 115 Ivory, 30ml Colour:115 Ivory   Its
     ]
    }
   ],
   "source": [
    "# convert data into dataset\n",
    "df = {'product_desc': data['product_description'], 'label': data['label']}\n",
    "from datasets import Dataset\n",
    "out_df = Dataset.from_dict(df)\n",
    "\n",
    "print(out_df[:2])\n",
    "\n",
    "#load a DistilBERT tokenizer, tokeniztation of the words\n",
    "from transformers import AutoTokenizer\n",
    "# using the distilbert tokenizer \n",
    "tokenizer = AutoTokenizer.from_pretrained(\"distilbert-base-uncased\", return_tensors='pt')\n",
    "\n",
    "#tokenization function\n",
    "# truncate sequences longer than DistilBERT?s maximum input length\n",
    "\n",
    "def tokenize(data):\n",
    "    return tokenizer(data[\"product_desc\"], truncation=True)\n",
    "\n",
    "#splitting dataset into train and test:\n",
    "train = out_df[:1000]\n",
    "test =  out_df[1000:1100]\n",
    "train = Dataset.from_dict(train)\n",
    "test = Dataset.from_dict(test)\n",
    "\n",
    "\n",
    "print(train[:2])\n",
    "print(test[:2])\n",
    "\n"
   ]
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   "source": [
    "print(test['label'])"
```

```
   ]
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   "id": "9edc1afe",
   "metadata": {},
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       "('tokenizer\\\\tokenizer_config.json',\n",
       " 'tokenizer\\\\special_tokens_map.json',\n",
       " 'tokenizer\\\\vocab.txt',\n",
       " 'tokenizer\\\\added_tokens.json',\n",
       " 'tokenizer\\\\tokenizer.json')"
      ]
     },
     "execution_count": 3,
     "metadata": {},
     "output_type": "execute_result"
    }
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    "from transformers import AutoTokenizer, AutoModelForSequenceClassification\n",
    "tokenizer.save_pretrained(\"tokenizer\")"
   ]
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       "model_id": "08e9ece439b946859faa2aea4291d087",
       "version_major": 2,
       "version_minor": 0
      },
      "text/plain": [
       "  0%|          | 0/1 [00:00<?, ?ba/s]"
      ]
     },
     "metadata": {},
     "output_type": "display_data"
    },
    {
     "data": {
      "application/vnd.jupyter.widget-view+json": {
       "model_id": "a6023076d538491e999bb46768d8d5a5",
       "version_major": 2,
       "version_minor": 0
      },
      "text/plain": [
       "  0%|          | 0/1 [00:00<?, ?ba/s]"
      ]
     },
     "metadata": {},
     "output_type": "display_data"
    }
   ],
   "source": [
    "# tokenizing train and test sets using map function, to avoid creating tokenizers.Encoding objects and keep dict or Data
    "# objects with keys\n",
    "train_tokens = train.map(tokenize, batched=True)\n",
    "test_tokens= test.map(tokenize, batched=True)\n"
   ]
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    "from transformers import DataCollatorWithPadding\n",
    "data_collator = DataCollatorWithPadding(tokenizer=tokenizer)"
   ]
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    "# defining a function to calculate prediction performance of the model:  'accuracy' metric will be used\n",
    "\"\n",
    "import numpy as np\n",
    "import evaluate\n",
    "\"\n",
    "accuracy = evaluate.load(\"accuracy\")\n",
    "def acc_calculate(pred):\n",
    "    predicted, actual = pred\n",
    "    predicted = np.argmax(predicted, axis=1)# argmax returns indices of the maximum values along axis 1; \n",
    "    # predicted contains the probabilities of all classes for each entry in the dataset,\n",
    "    # the index 0 means that probabilty of class 0 is the highst and so on..\n",
    "    return accuracy.compute(predictions=predicted, references=actual)\n",
    "\"\n",
    "# create a map of the expected ids to their labels with id2label and label2id:\n",
```

```
    "\n",
    "id2label = {0: \"Electronics\", 1: \"Household\", 2: \"Books\", 3:\"Clothing & Accessories\"}\n",
    "label2id = {\"Electronics\": 0, \"Household\": 1, \"Books\":2, \"Clothing & Accessories\":3}\n",
    "\n",
    "## stop here if you are running the code on cpu; this will take around 90 Min. Use the pretraind model below.."
   ]
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      "\n",
      "All the weights of DistilBertForSequenceClassification were initialized from the TF 2.0 model.\n",
      "If your task is similar to the task the model of the checkpoint was trained on, you can already use DistilBertForSequ
     ]
    }
   ],
   "source": [
    "#model = AutoModelForSequenceClassification.from_pretrained(\"distilbert-base-uncased\", num_labels=4, id2label=id2label
    "#)\n",
    "#model.save_pretrained(\"distilbert_model_uncased\")"
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      "\n",
      "All the weights of DistilBertForSequenceClassification were initialized from the TF 2.0 model.\n",
      "If your task is similar to the task the model of the checkpoint was trained on, you can already use DistilBertForSequ
     ]
    }
   ],
   "source": [
    "# defining the transformer\n",
    "#from_pretrained(): to load the pretrained Bert model weights\n",
    "#AutoModelForSequenceClassification: is a generic sequence classification model that will be instantiated using a preta
    "\n",
    "transformer = AutoModelForSequenceClassification.from_pretrained(\n",
    "\"distilbert-base-uncased\", num_labels=4, id2label=id2label, label2id=label2id, from_tf=True\n",
    ")"
   ]
  },
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   "outputs": [],
   "source": [
    "# defining the training parameters\n",
    "training_pars = TrainingArguments(\n",
    "    output_dir=\"my_transformer\",\n",
    "    per_device_train_batch_size=128,\n",
    "    per_device_eval_batch_size=128,\n",
    "    num_train_epochs=1,\n",
    "    weight_decay=0.01,\n",
    "    evaluation_strategy=\"epoch\",\n",
    "    save_strategy=\"epoch\",\n",
    "    load_best_model_at_end=True)\n",
    "\n",
    "# defining the trainer of the model\n",
    "#The Trainer class provides an API for feature-complete training in PyTorch\n",
    "trainer = Trainer(\n",
    "    model=transformer,\n",
    "    args=training_pars,\n",
    "    train_dataset= train_tokens,\n",
    "    eval_dataset=test_tokens,\n",
    "    tokenizer=tokenizer,\n",
    "    data_collator=data_collator,\n",
    "    compute_metrics=acc_calculate,\n",
    ")\n",
    "#training the transformer\n",
    "trainer.train()"
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    "#trainer.save_model(\"./Distilbert_based_transformer\")\n",
    "\n",
    "# evaluate the model \n",
    "result =trainer.evaluate()\n",
```

```
    "result"
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    "transformer_trained = AutoModelForSequenceClassification.from_pretrained(\"./Distilbert_based_transformer\") "
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      "  warnings.warn(\n"
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       "  {'label': 'Books', 'score': 0.017655229195952415},\n",
       "  {'label': 'Clothing & Accessories', 'score': 0.014185710810124874}]]"
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    "from transformers import TextClassificationPipeline\n",
    "# This pipeline has a return_all_scores parameter on its __call__ method that allows you to get all scores for each lab
    "pipe = TextClassificationPipeline(model=transformer_trained, tokenizer=tokenizer)\n",
    "prediction = pipe(\"NetGen 4k Wi-Fi 16 MP Ultra HD Action Camera\", return_all_scores=True)\n",
    "prediction"
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    "# using GPT-2 to generate text\n",
    "from transformers import pipeline\n",
    "text_generator = pipeline('text-generation', model='gpt2')\n",
    "# generate 5 different sentences by sampling from the top 10 hits:\n",
    "#Temperature is a hyper-parameter used to control the randomness of predictions by scaling the logits before applying s
    "# when temperature is a large value (e.g. 1), the GPT-2 model produces more diversity and also more mistakes and viseve
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    "for sent in sentences:\n",
    "  print(sent[\"generated_text\"])\n",
    "  print(\"#\"*50)"
   ]
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Distilbert_based_transformer.rar (248.37 MB)