

# NER – Named Entity Recognition

Github URL- <https://github.com/TheDevCarnage/NLP-Project-NER.git>

My Github (my contributions/progress)- [https://github.com/asb1996/NER-Project\\_NLP.git](https://github.com/asb1996/NER-Project_NLP.git)

## What is NER?

Named entity recognition (NER) is a fundamental task in Natural Language Processing (NLP) and one of the first stages in many language understanding tasks.

## Problem We are Solving?

We are using eBay listing titles for NER. A few examples of NER labeling of listing titles are shown below (these examples are in English to illustrate the concept, the challenge data will have German language listing titles).



## About Data

- 10 million randomly selected unlabeled item titles from eBay Germany, "Athletic Shoes" categories.
  - 10,000 labeled item titles provided.
- Context
  - "New" tagged as "No Tag" in "New shoes", but "Marke" (brand) in "New Balance".
- Misspellings
- No Tag
  - Punctuation, and words adding no meaning (black & white), prepositions.
- Obscure
  - Un-deciphered

**\*You can refer to the Annexure.pdf file for more information on the dataset.**

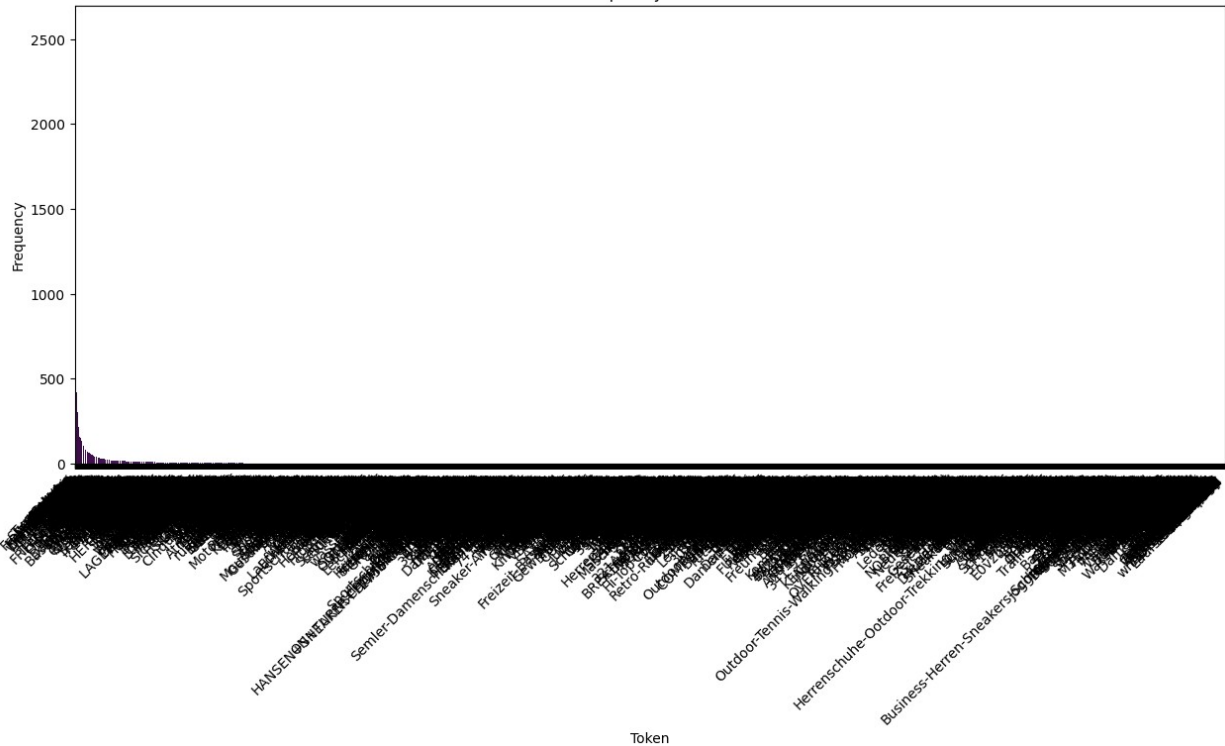
## Sample

Record Number	Title	Token	Tag
1	Supreme Nike SB Dunk High By any Means Red US10 EU44 Supreme Box Logo Air Force	Supreme	Modell
1	Supreme Nike SB Dunk High By any Means Red US10 EU44 Supreme Box Logo Air Force	Nike	Marke
1	Supreme Nike SB Dunk High By any Means Red US10 EU44 Supreme Box Logo Air Force	SB	Produktlinie
1	Supreme Nike SB Dunk High By any Means Red US10 EU44 Supreme Box Logo Air Force	Dunk	
1	Supreme Nike SB Dunk High By any Means Red US10 EU44 Supreme Box Logo Air Force	High	Schuhschaft-Typ
1	Supreme Nike SB Dunk High By any Means Red US10 EU44 Supreme Box Logo Air Force	By	Modell
1	Supreme Nike SB Dunk High By any Means Red US10 EU44 Supreme Box Logo Air Force	any	
1	Supreme Nike SB Dunk High By any Means Red US10 EU44 Supreme Box Logo Air Force	Means	
1	Supreme Nike SB Dunk High By any Means Red US10 EU44 Supreme Box Logo Air Force	Red	Farbe
1	Supreme Nike SB Dunk High By any Means Red US10 EU44 Supreme Box Logo Air Force	US10	US-Schuhgröße
1	Supreme Nike SB Dunk High By any Means Red US10 EU44 Supreme Box Logo Air Force	EU44	EU-Schuhgröße
1	Supreme Nike SB Dunk High By any Means Red US10 EU44 Supreme Box Logo Air Force	Supreme	No Tag
1	Supreme Nike SB Dunk High By any Means Red US10 EU44 Supreme Box Logo Air Force	Box	No Tag
1	Supreme Nike SB Dunk High By any Means Red US10 EU44 Supreme Box Logo Air Force	Logo	Akzente
1	Supreme Nike SB Dunk High By any Means Red US10 EU44 Supreme Box Logo Air Force	Air	Produktlinie
1	Supreme Nike SB Dunk High By any Means Red US10 EU44 Supreme Box Logo Air Force	Force	

## **Data Visualization**

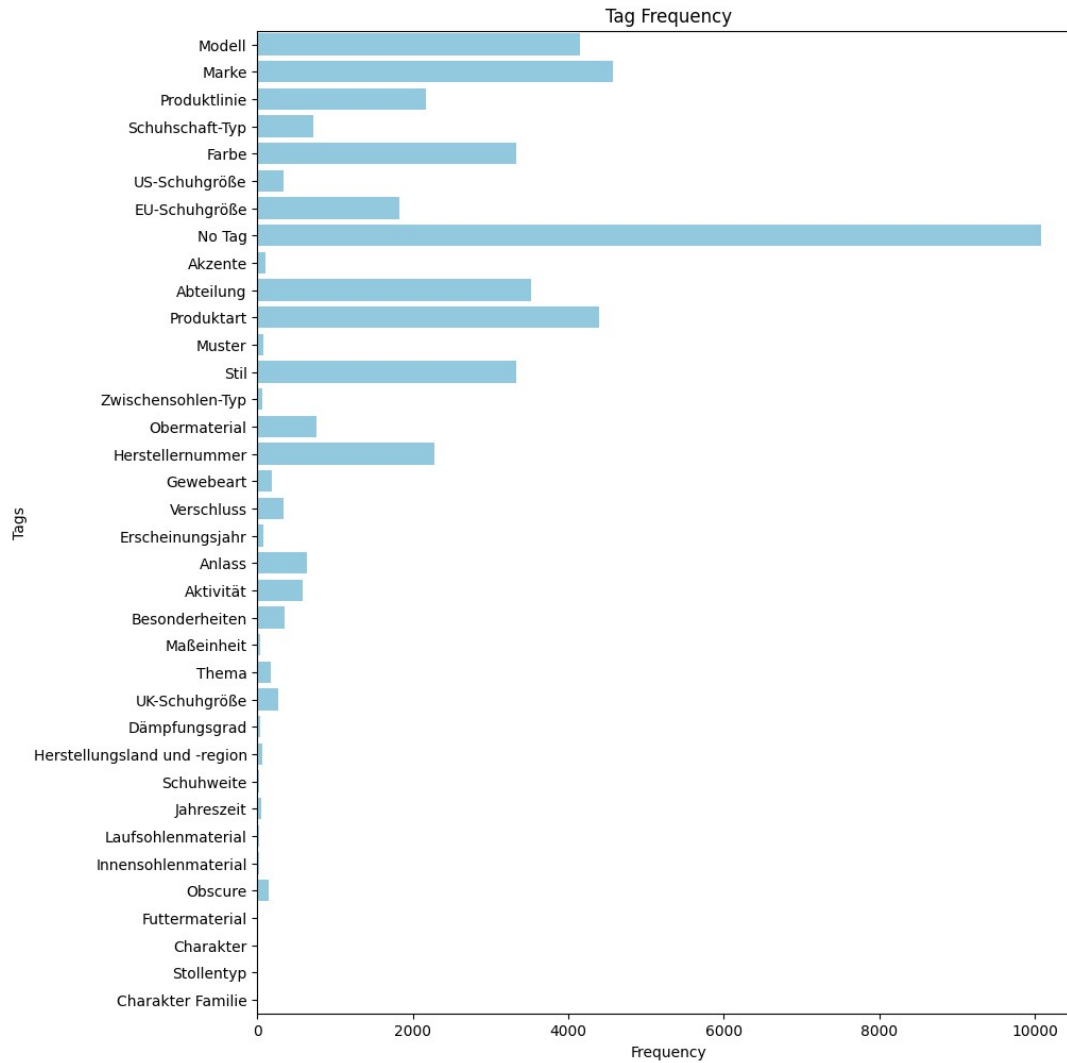
We visualized data to understand what features need to be extracted. Some techniques were better than others. Below a frequency chart for tokens was a bad approach so we pivoted towards word cloud. Following it you will find the word cloud and frequency chart for tags and after that the word cloud for all the tokens in the title.

Token Frequency in sentences



Token









- Tokenization
- Attention Mask (Specific to Bert)
- Padding/Truncation
- Punctuation
- Label Encoding
- BERT Specific Input Format

```

tokenizerbert = BertTokenizer.from_pretrained('bert-base-uncased')
tokensbert= tokenizerbert(''.join(modelsteptokens), return_tensors='pt')
input_ids = tokensbert['input_ids']

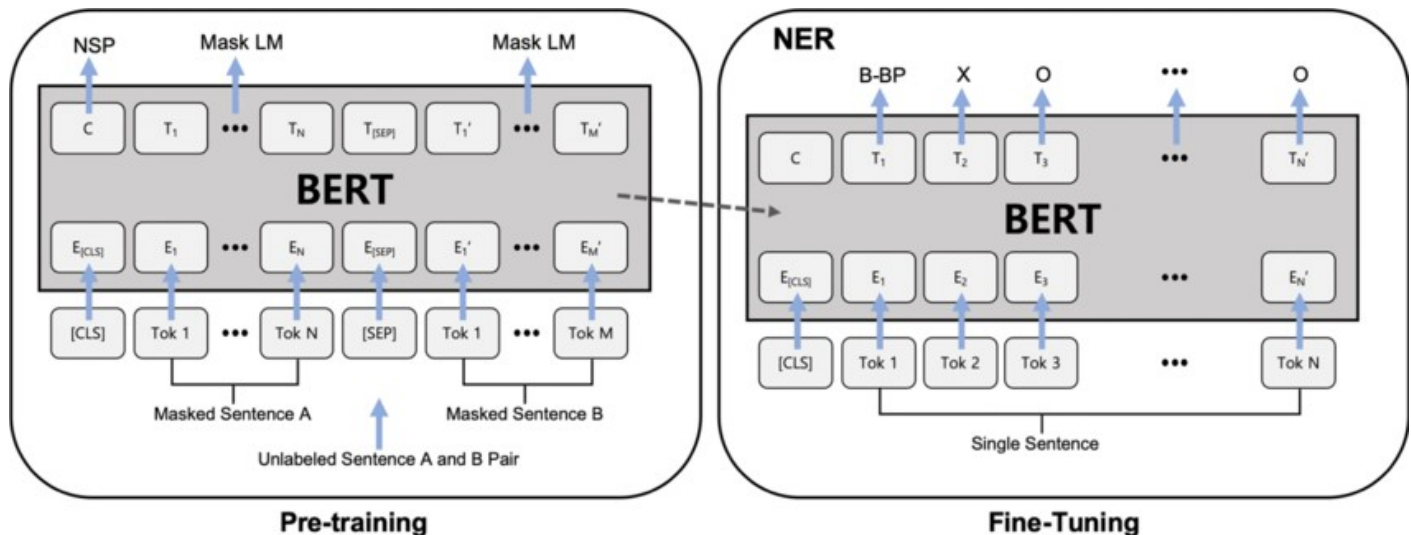
attention_mask = [1] * len(input_ids)

label_ids = [tokenizerbert.convert_tokens_to_ids(tag) for tag in modelsteptags]
label_attention_mask = [1 if label_id != tokenizerbert.pad_token_id else 0 for label_id in label_ids]

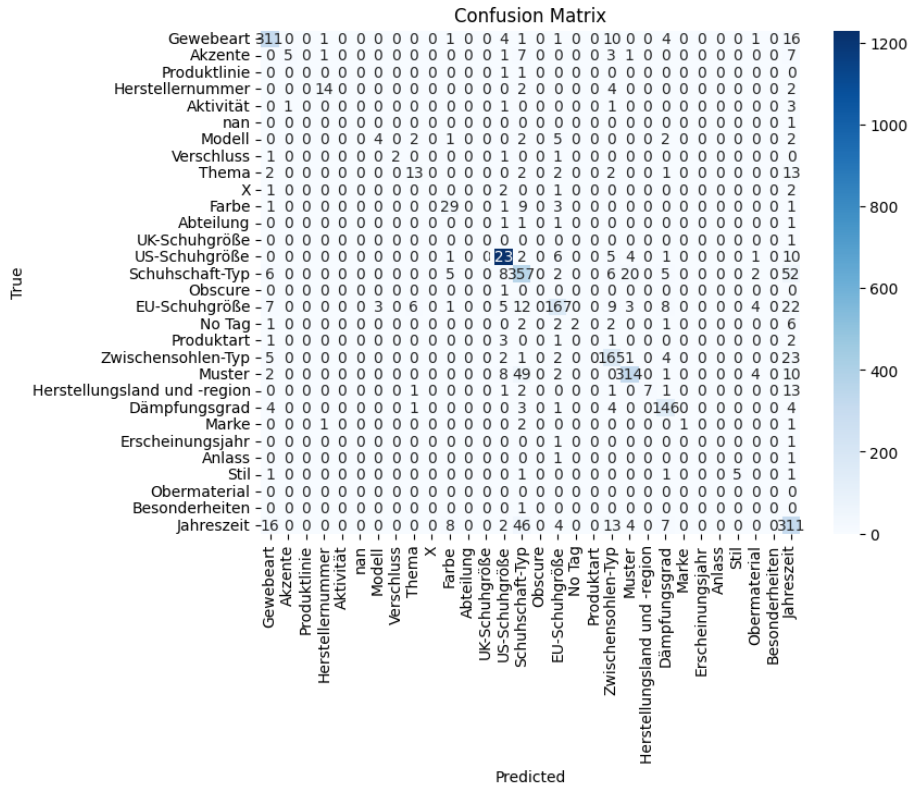
input_ids_tensor = input_ids.unsqueeze(0)
attention_mask_tensor = torch.tensor([attention_mask])
label_ids_tensor = torch.tensor([label_ids])
label_attention_mask_tensor = torch.tensor([label_attention_mask])

```

## Modeling with BERT



We used 'bert-base-german-cased' to tokenize and pre train the model with our dataset from Train\_Tagged\_Titles.tsv. Following is the confusion matrix and the F1 scores. Also attached with the submission will be a folder I wrote to to store the accuracy/recall/f1\_score information. I have updated the confusion matrix from the project presentation day therefore it is different. However due to lack of time I was unable to plot the validation loss graph.





\*\*\*\*\* Eval results \*\*\*\*\*

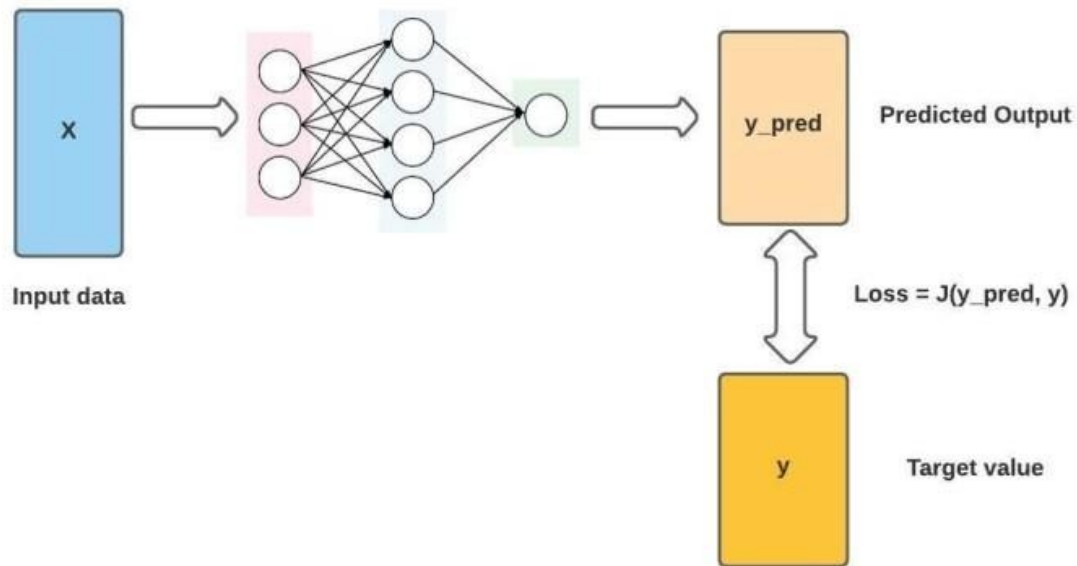
	precision	recall	f1-score	support
Schuhgröße	0.5714	0.1818	0.2759	22
Typ	1.0000	0.2593	0.4118	27
_	0.0000	0.0000	0.0000	0
ahreszeit	0.0000	0.0000	0.0000	1
an	0.5796	0.6354	0.6062	384
arbe	0.5714	0.3429	0.4286	35
arke	0.9652	0.9706	0.9679	1257
bteilung	0.8592	0.8592	0.8592	348
erschluss	1.0000	0.5556	0.7143	9
erstellernummer	0.6000	0.5455	0.5714	44
esonderheiten	0.0000	0.0000	0.0000	6
ewebeart	0.0000	0.0000	0.0000	6
hema	1.0000	0.2000	0.3333	5
ktivität	0.8333	0.2000	0.3226	25
kzente	0.0000	0.0000	0.0000	2
nlass	0.8235	0.6364	0.7179	22
o Tag	0.7771	0.6239	0.6921	218
odell	0.7038	0.7251	0.7143	462
region	0.0000	0.0000	0.0000	4
roduktart	0.7214	0.7143	0.7178	203
roduktlinie	0.9012	0.7969	0.8458	389
rscheinungsjahr	1.0000	0.4000	0.5714	5
til	0.8022	0.8957	0.8464	163
uster	0.0000	0.0000	0.0000	1
ämpfungsggrad	0.0000	0.0000	0.0000	1
micro avg	0.8262	0.7994	0.8126	3639
macro avg	0.5484	0.3817	0.4239	3639
weighted avg	0.8247	0.7994	0.8063	3639

f1 socre: 0.812570

Accuracy score: 0.827429

Cross entropy loss is given in BERT Model is given by

$$\ell(x, y) = L = \{l_1, \dots, l_N\}^T, \quad l_n = -w_{y_n} \log \frac{\exp(x_{n,y_n})}{\sum_{c=1}^C \exp(x_{n,c})} \cdot 1.$$



Below is a picture of our poster from project presentation:

