

Classificação de Avaliações de Produtos

Projeto NLP - Deep Learning

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Especialização
Deep Learning



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Objetivo

Automatizar e classificar os reviews de produtos em scores.



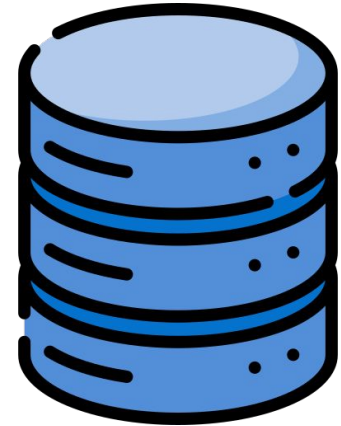
Introdução



- Base de Dados da Olist de avaliações de produtos comercializados (Kaggle)
- Olist é uma startup Brasileira de tecnologia para varejo
 - Gestão de Lojas offline e online (e-commerce)
 - MercadoLivre, Americanas e Amazon
 - Loja Única
 - 30 mil lojistas
 - 2 milhões de consumidores únicos a cada ano
- Avaliações de produtos de telefonia



Base de Dados



- Join 4 bases
 - Itens por pedido
 - Reviews de pedidos
 - Pedidos
 - Produtos
- Filtrar categoria Telefonia
- 2050 Reviews de produtos de Telefonia

- Limpeza e eliminação comentários Null e espaço vazio

Data columns (total 5 columns):

#	Column	Non-Null Count	Dtype
0	review_id	2050 non-null	object
1	product_category_name	2050 non-null	object
2	review_score	2050 non-null	int64
3	review_comment_title	440 non-null	object
4	review_comment_message	2050 non-null	object

Score : 1

Quantidade de Reviews com score 1: 453

Percentual de Reviews com score 1: 22.097560975609756 %

Exemplo de Reviews : A película não é de gel. É de plástico e a capa é de plástico de um material péssimo.

Tive que jogar no lixo.

Score : 2

Quantidade de Reviews com score 2: 130

Percentual de Reviews com score 2: 6.341463414634147 %

Exemplo de Reviews : Comprei dois produtos e veio só um

Score : 3

Quantidade de Reviews com score 3: 205

Percentual de Reviews com score 3: 10.0 %

Exemplo de Reviews : solicitei a devolução mesmo assim me mandarão e mandarão errado

Score : 4

Quantidade de Reviews com score 4: 348

Percentual de Reviews com score 4: 16.975609756097562 %

Exemplo de Reviews : Produto foi encontrado com um bom preço no site e entregue bem rapido.

Score : 5

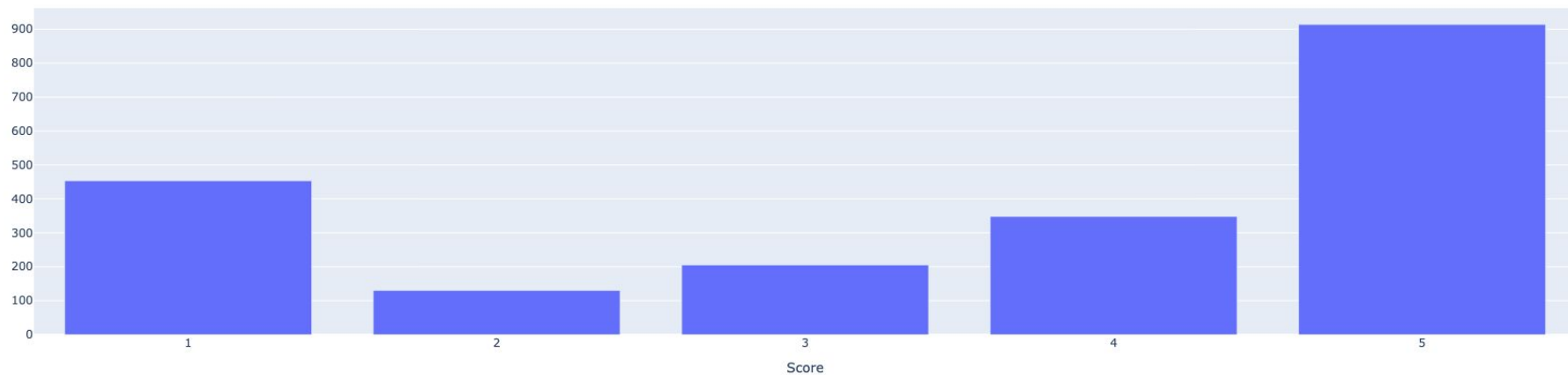
Quantidade de Reviews com score 5: 914

Percentual de Reviews com score 5: 44.58536585365854 %

Exemplo de Reviews : Produto de excelente qualidade

Quantidade total de reviews : 2050

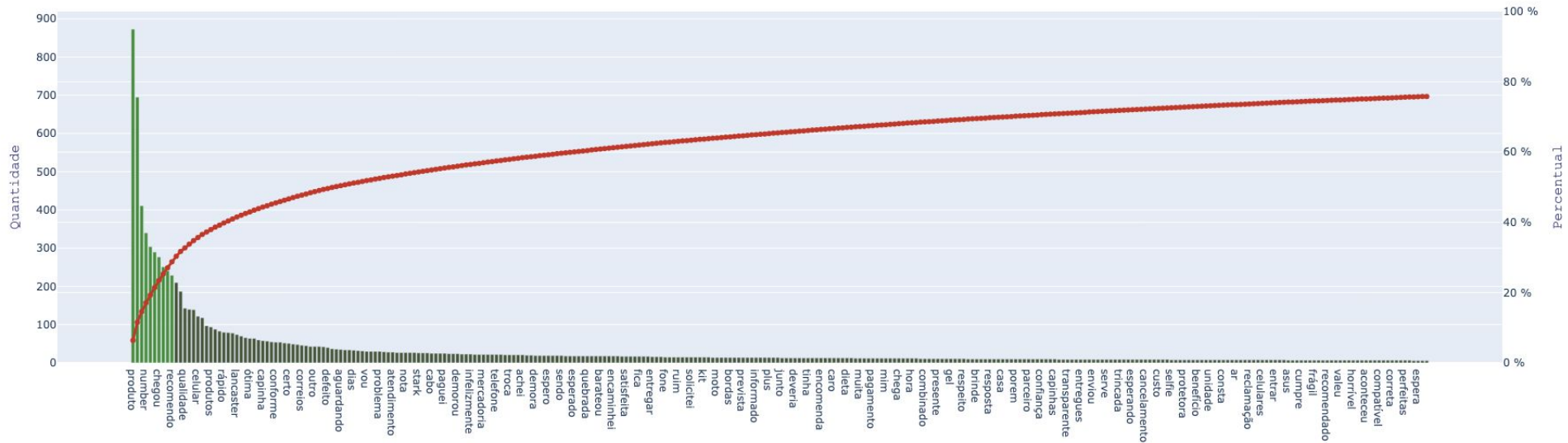
Quantidade de Reviews por Score



Pré-Processamento

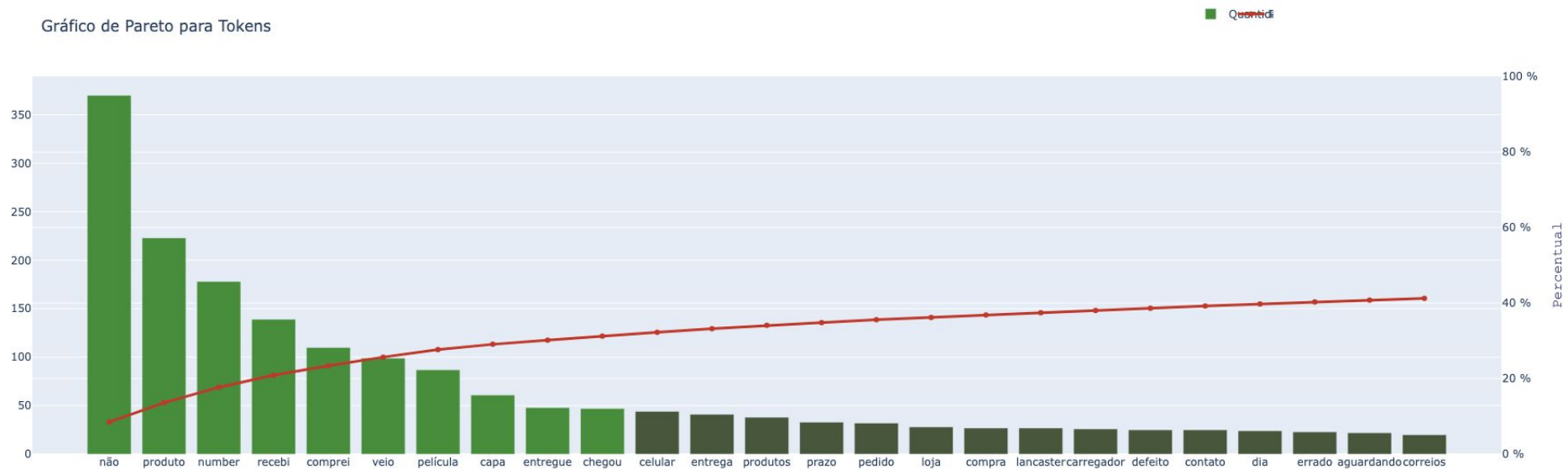
- Emoji, caracteres especiais e palavras escritas abreviadas
- Normalização palavras
- Maiúscula nomes próprios, começo de frase e acrônimos
- Retirar Stop Words, pontuação, dígitos, moedas e símbolos especiais.
- Manter o não devido a importância

Quantidi



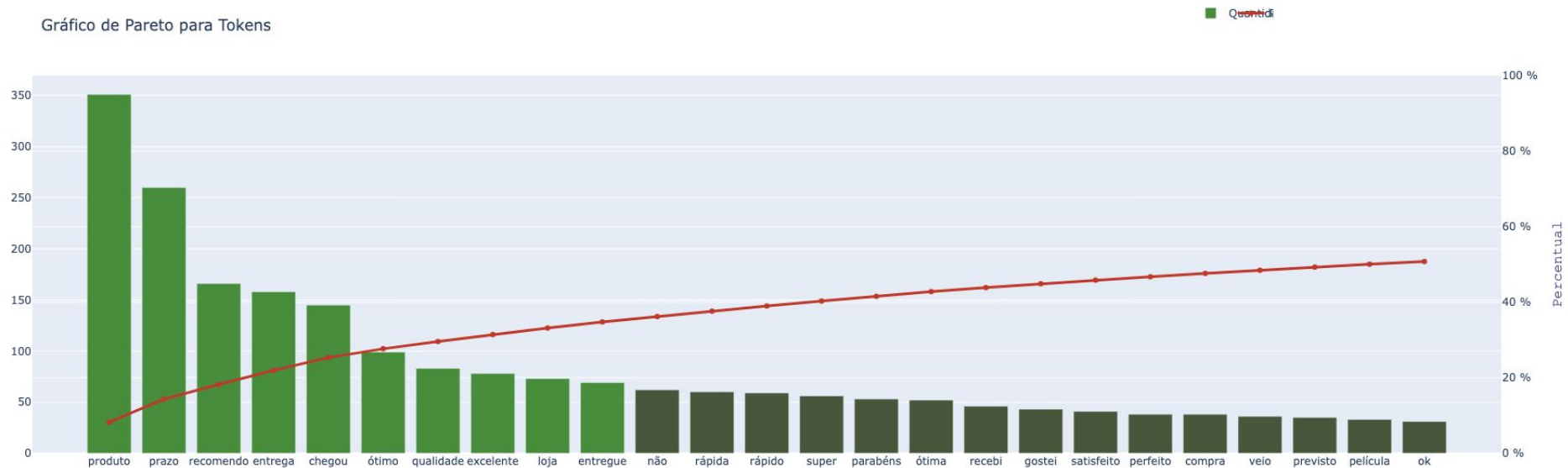
Pareto Score 1

Gráfico de Pareto para Tokens

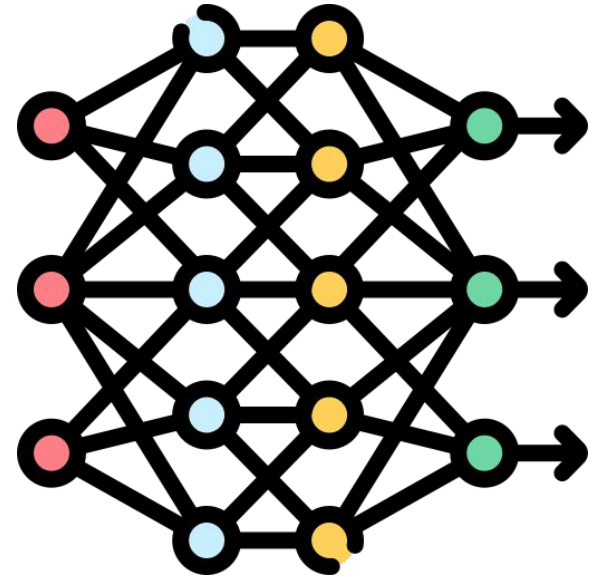


Pareto Score 5

Gráfico de Pareto para Tokens

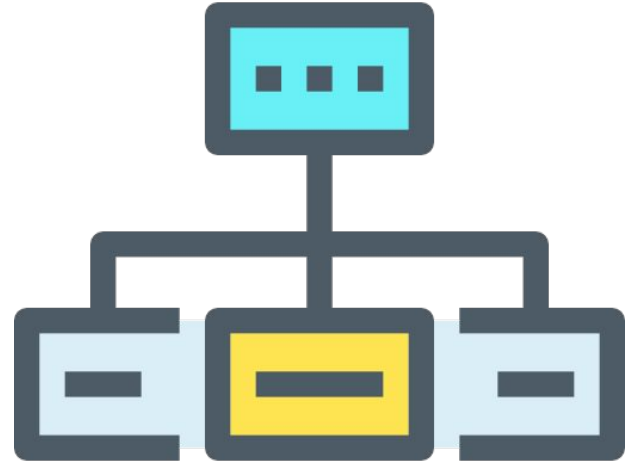


Modelos



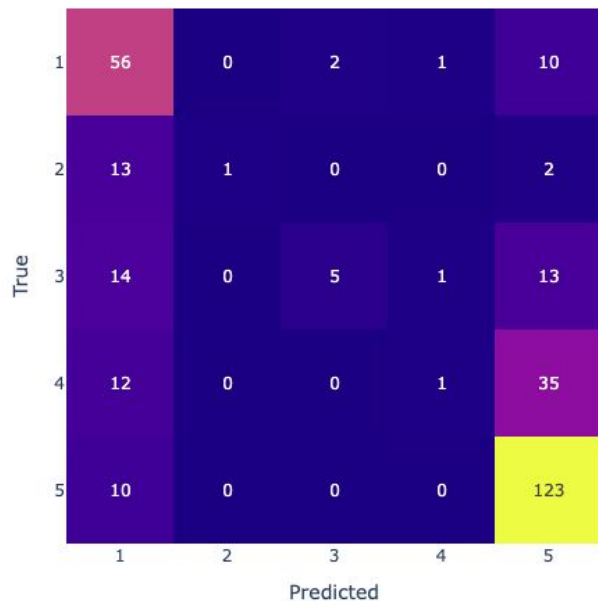
Treino, Validação e Teste

- 70% Treino
- 15% Validação
- 15% Teste



SVM + BoW

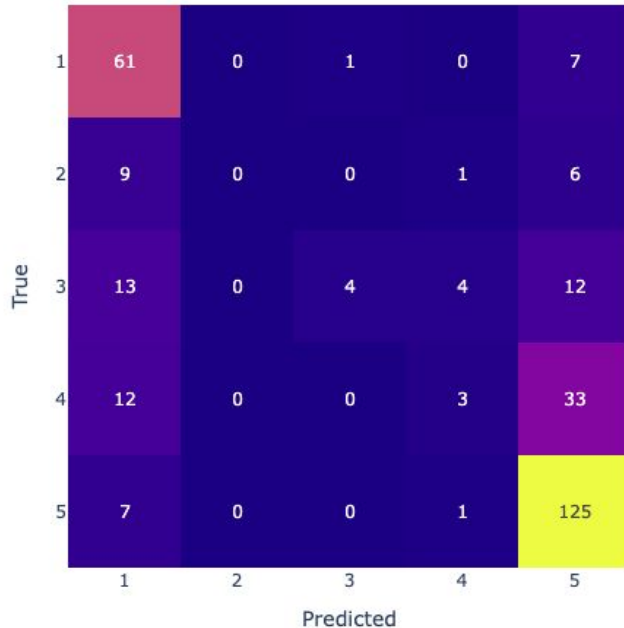
- CountVectorizer



	precision	recall	f1-score	support
1	0.53	0.81	0.64	69
2	1.00	0.06	0.12	16
3	0.71	0.15	0.25	33
4	0.33	0.02	0.04	48
5	0.67	0.92	0.78	133
accuracy			0.62	299
macro avg	0.65	0.39	0.37	299
weighted avg	0.61	0.62	0.54	299

SVM + TFIDF Unigrams

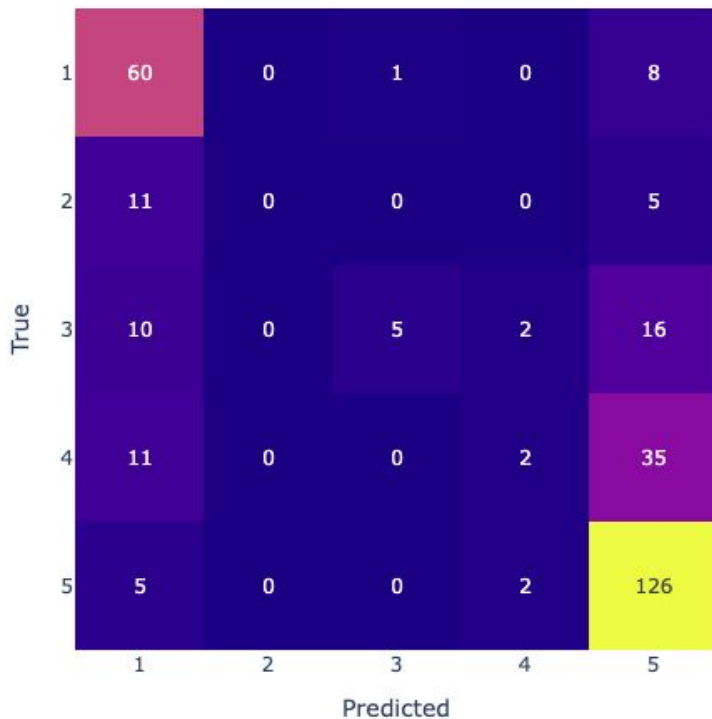
- TfidfVectorizer Unigrams



	precision	recall	f1-score	support
1	0.60	0.88	0.71	69
2	0.00	0.00	0.00	16
3	0.80	0.12	0.21	33
4	0.33	0.06	0.11	48
5	0.68	0.94	0.79	133
accuracy			0.65	299
macro avg	0.48	0.40	0.36	299
weighted avg	0.58	0.65	0.56	299

SVM + TFIDF BiGrams

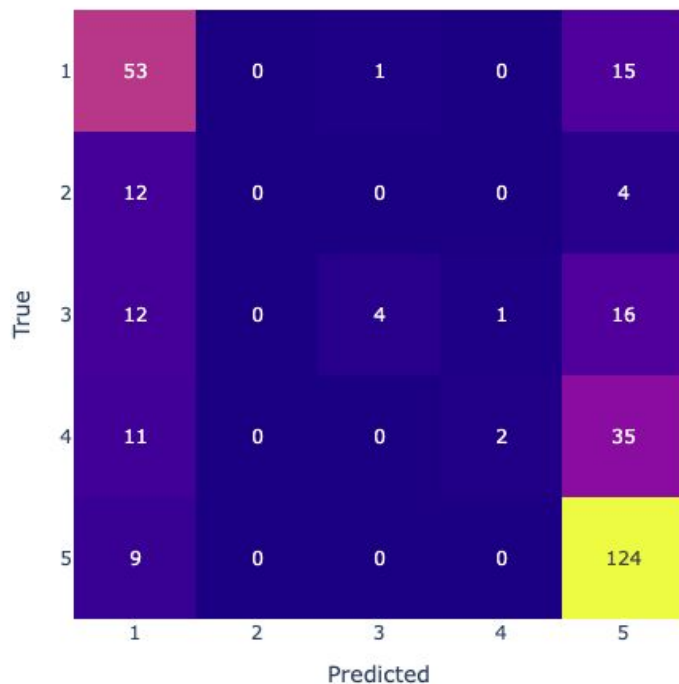
- TfidfVectorizer Bigrams



	precision	recall	f1-score	support
1	0.62	0.87	0.72	69
2	0.00	0.00	0.00	16
3	0.83	0.15	0.26	33
4	0.33	0.04	0.07	48
5	0.66	0.95	0.78	133
accuracy			0.65	299
macro avg	0.49	0.40	0.37	299
weighted avg	0.58	0.65	0.55	299

SVM + CBOW 300

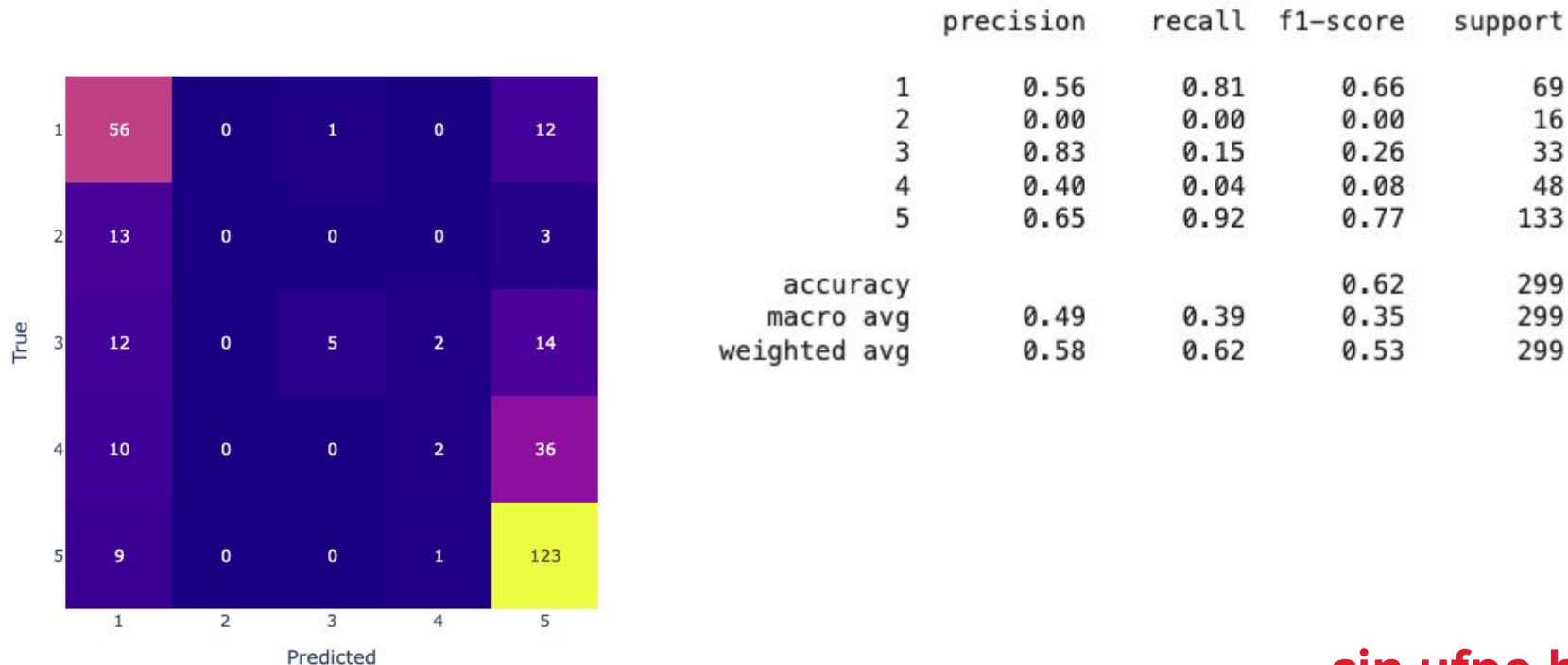
- Embedding Word2Vector CBOW 300 (NILC - USP)



	precision	recall	f1-score	support
1	0.55	0.77	0.64	69
2	0.00	0.00	0.00	16
3	0.80	0.12	0.21	33
4	0.67	0.04	0.08	48
5	0.64	0.93	0.76	133
accuracy			0.61	299
macro avg	0.53	0.37	0.34	299
weighted avg	0.61	0.61	0.52	299

SVM + SKIP 300

- Embedding Word2Vector Skip-Gram 300 (NILC - USP)



BERT

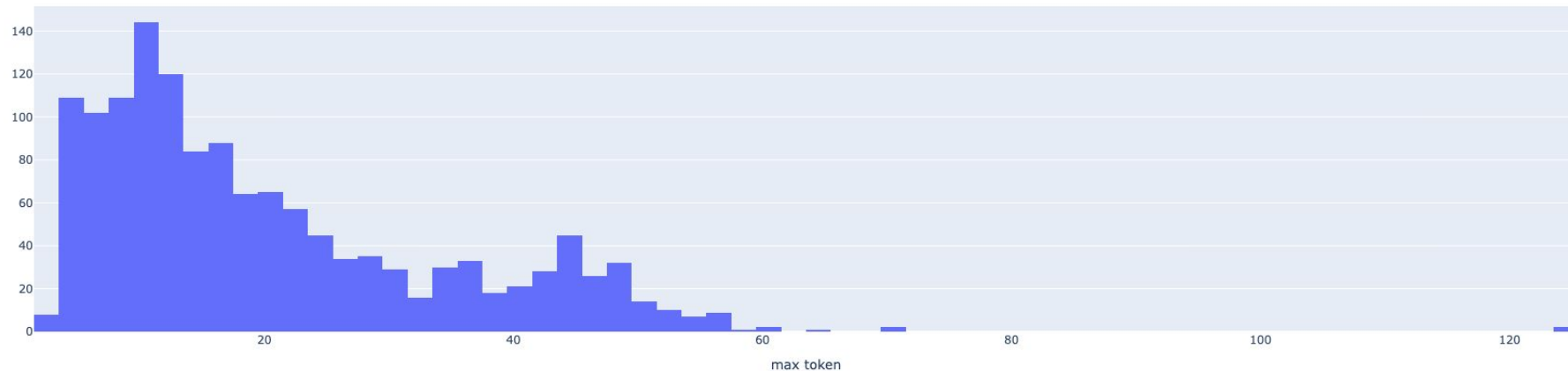
- BERTimbau (Pré-Treinado em Português) (NeuralMind)
- Tokenização
- Histograma Quantidade de Tokens



BERT

- Tokenização 165 tokens

Histograma Quantidade de Tokens



BERT

- Arquitetura BERT (Pooling Embedding) (765) + 1 camada de 1500 + 1 camada de saída de 5
- DropOut de 30%
- BatchNormalization
- CrossEntropyLoss
- Softmax
- Penalização de Pesos no treinamento (Desbalanceamento)

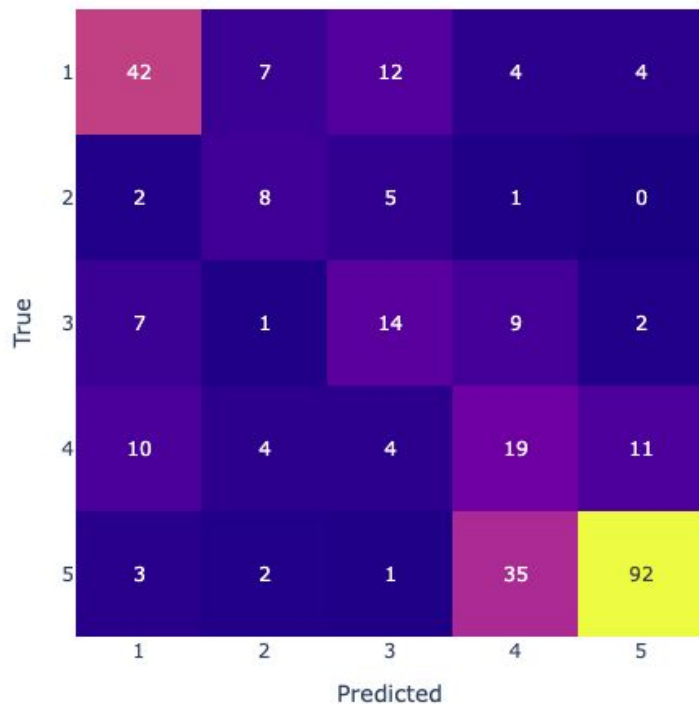
BERT

```
Bert(
  (bertimbau): BertModel(
    (embeddings): BertEmbeddings(
      (word_embeddings): Embedding(29794, 768, padding_idx=0)
      (position_embeddings): Embedding(512, 768)
      (token_type_embeddings): Embedding(2, 768)
      (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
      (dropout): Dropout(p=0.1, inplace=False)
    )
    (encoder): BertEncoder(
      (layer): ModuleList(
        (0-11): 12 x BertLayer(
          (attention): BertAttention(
            (self): BertSdpaSelfAttention(
              (query): Linear(in_features=768, out_features=768, bias=True)
              (key): Linear(in_features=768, out_features=768, bias=True)
              (value): Linear(in_features=768, out_features=768, bias=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
            (output): BertSelfOutput(
              (dense): Linear(in_features=768, out_features=768, bias=True)
              (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
              (dropout): Dropout(p=0.1, inplace=False)
            )
          )
          (intermediate): BertIntermediate(
            (dense): Linear(in_features=768, out_features=3072, bias=True)
            (intermediate_act_fn): GELUActivation()
          )
          (output): BertOutput(
            (dense): Linear(in_features=3072, out_features=768, bias=True)
            (LayerNorm): LayerNorm((768,), eps=1e-12, elementwise_affine=True)
            (dropout): Dropout(p=0.1, inplace=False)
          )
        )
      )
    )
    (pooler): BertPooler(
      (dense): Linear(in_features=768, out_features=768, bias=True)
      (activation): Tanh()
    )
  )
  (dropout): Dropout(p=0.3, inplace=False)
  (batch_normalization): BatchNorm1d(768, eps=1e-05, momentum=0.1, affine=True, track_running_stats=True)
  (head_classification): Sequential(
    (0): Linear(in_features=768, out_features=1500, bias=True)
    (1): Linear(in_features=1500, out_features=5, bias=True)
  )
  (loss): CrossEntropyLoss()
)
```

BERT

Layer (type:depth-idx)	Param #
—BertModel: 1-1	(108,923,136)
—Dropout: 1-2	—
—BatchNorm1d: 1-3	1,536
—Sequential: 1-4	1,161,005
—CrossEntropyLoss: 1-5	—
Total params: 110,085,677	
Trainable params: 1,162,541	
Non-trainable params: 108,923,136	
Layer (type:depth-idx)	Param #
—BertModel: 1-1	(108,923,136)
—Dropout: 1-2	—
—BatchNorm1d: 1-3	1,536
—Sequential: 1-4	1,161,005
—CrossEntropyLoss: 1-5	—
Total params: 110,085,677	
Trainable params: 1,162,541	
Non-trainable params: 108,923,136	

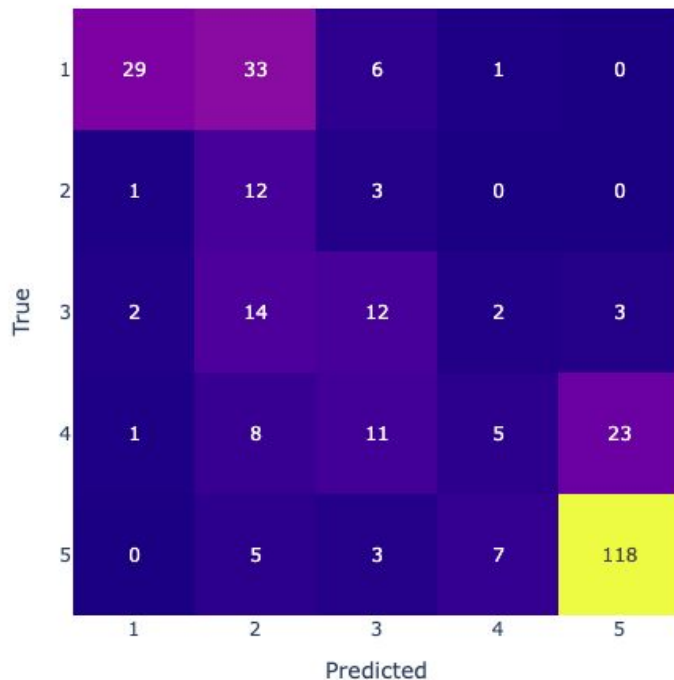
BERT



	precision	recall	f1-score	support
1	0.66	0.61	0.63	69
2	0.36	0.50	0.42	16
3	0.39	0.42	0.41	33
4	0.28	0.40	0.33	48
5	0.84	0.69	0.76	133
accuracy			0.59	299
macro avg	0.51	0.52	0.51	299
weighted avg	0.63	0.59	0.60	299

LLM GPT-4 Mini

- OpenAI
- Prompt Contexto + Exemplos



	precision	recall	f1-score	support
1	0.88	0.42	0.57	69
2	0.17	0.75	0.27	16
3	0.34	0.36	0.35	33
4	0.33	0.10	0.16	48
5	0.82	0.89	0.85	133
accuracy			0.59	299
macro avg	0.51	0.51	0.44	299
weighted avg	0.67	0.59	0.59	299

Resultados e Conclusão

	model	accuracy	f1_score
0	SVM + BoW	0.622074	0.365804
1	SVM + TFIDF unigrams	0.645485	0.364076
2	SVM + TFIDF bigrams	0.645485	0.366712
3	SVM + Word2Vector CBOW 300	0.612040	0.337184
4	SVM + Word2Vector SKIP 300	0.622074	0.352192
5	BERTimbau Base	0.585284	0.509269
6	LLM GPT-4 mini	0.588629	0.441002

Obrigado

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