

Escuela Profesional de Ciencia de la Computacion



CLASIFICACION DE REQUISITOS DE SOFTWARE

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Proyecto Final de Carrera 1



DEFINICION DEL PROBLEMA



Problema

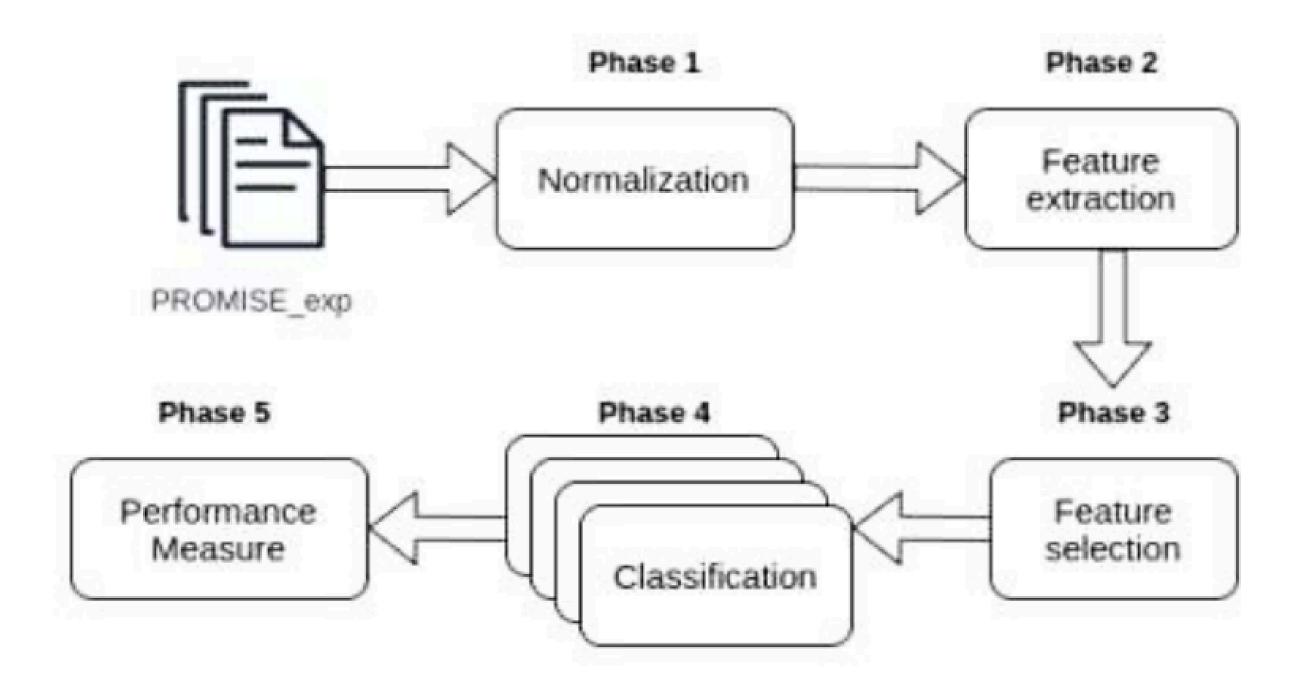
La **naturaleza ambigua e inconsistente del lenguaje natural dificulta la tarea de clasificacion de requisitos de software,** generando interpretaciones variadas y, en consecuencia, problemas de precisión y coherencia en la categorización.

Desafios

- Limitación de conjuntos de datos existentes
- Falta de métricas estándar
- Falta de transparencia en la metodología y ausencia de código

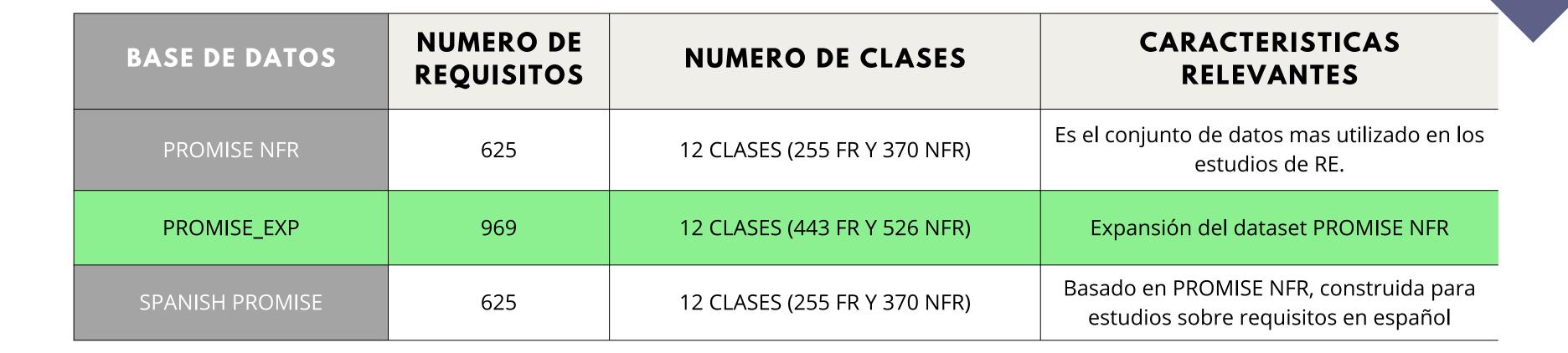
PIPELINE





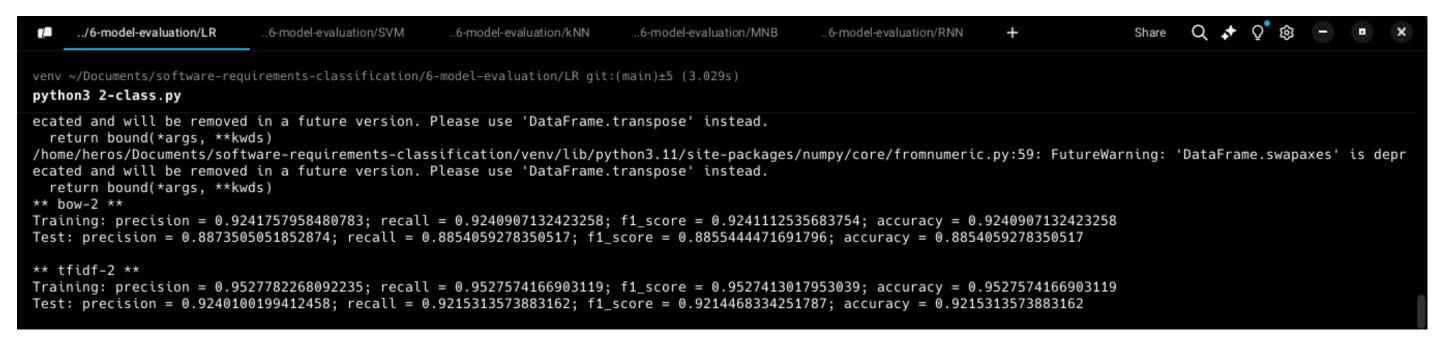


BASES DE DATOS

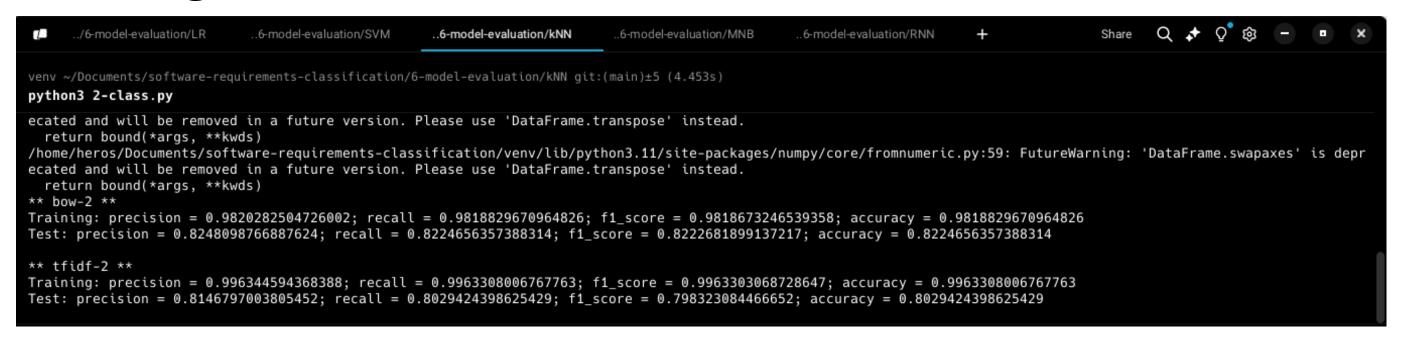




Regresion Logistica (LR)

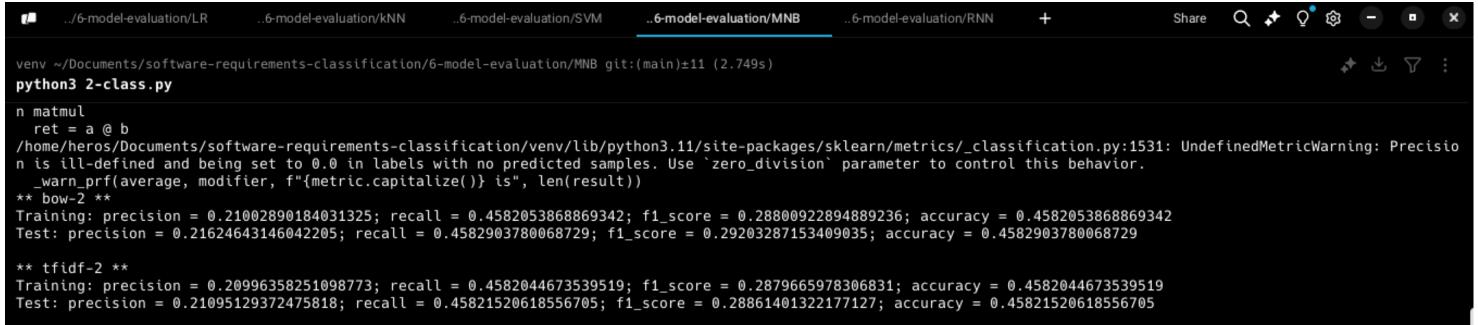


K-Nearest Neighboard(KNN)





Support Vector Machine (SVM)



Multinomial Naive Bayes (MNB)

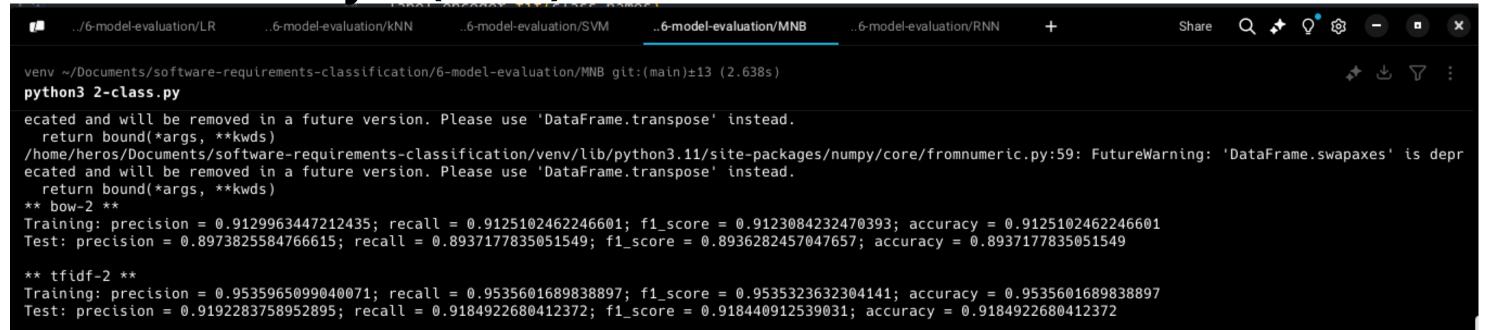






TABLE II RESULTADOS DE CLASIFICACIÓN BINARIA CON BOW Y TF-IDF PARA VARIOS MODELOS DE ML

Modelo	Vectorización	Entrenamiento				Prueba			
		Precisión	Recall	F1-Score	Exactitud	Precisión	Recall	F1-Score	Exactitud
LR	BoW	0.9242	0.9241	0.9241	0.9241	0.8874	0.8854	0.8855	0.8854
	TF-IDF	0.9528	0.9528	0.9527	0.9528	0.9240	0.9215	0.9214	0.9215
KNN	BoW	0.9820	0.9819	0.9819	0.9819	0.8248	0.8225	0.8223	0.8225
	TF-IDF	0.9963	0.9963	0.9963	0.9963	0.8147	0.8029	0.7983	0.8029
SVM	BoW	0.9663	0.9659	0.9660	0.9659	0.8692	0.8668	0.8668	0.8668
	TF-IDF	0.9901	0.9899	0.9899	0.9899	0.9009	0.8999	0.8999	0.8999
MNB	BoW	0.9130	0.9125	0.9123	0.9125	0.8974	0.8937	0.8936	0.8937
	TF-IDF	0.9536	0.9536	0.9535	0.9536	0.9192	0.9185	0.9184	0.9185



RNN (W2V + LSTM) y RNN (W2V + GRU)

```
venv ~/Documents/software-requirements-classification/6-model-evaluation/RNN git:(main)±36 (4h 18m 51s)
                                                                                                                                                         python3 2-class.py
40/40 -
Epoch 91/100
28/28 -
                         - 7s 235ms/step - loss: 0.3360
Epoch 92/100
28/28 —
                         7s 235ms/step - loss: 0.3264
Epoch 93/100
28/28 -
                         - 7s 240ms/step - loss: 0.3383
Epoch 94/100
28/28 -
                         - 7s 258ms/step - loss: 0.3381
Epoch 95/100
                          · 8s 268ms/step - loss: 0.2970
28/28 —
Epoch 96/100
28/28 -
                          7s 235ms/step - loss: 0.3366
Epoch 97/100
28/28 —
                         - 7s 242ms/step - loss: 0.3881
Epoch 98/100
28/28 -
                         - 7s 236ms/step - loss: 0.3635
Epoch 99/100
28/28 -
                         - 7s 237ms/step - loss: 0.3204
Epoch 100/100
28/28 ----
                         - 7s 238ms/step - loss: 0.3560
                        — 3s 111ms/step
3/3 —
                       0s 102ms/step
** 2-w2v-lstm **
Training: precision = 0.9486775567302452 +/- 0.008629155797389649; recall = 0.948288223672457 +/- 0.00893329651953777; f1_score = 0.9482279635103875 +/- 0.00902759671
4315033; accuracy = 0.948288223672457 +/- 0.00893329651953777
Test: precision = 0.8580150003782571 + - 0.033055955871817144; recall = 0.8524591924398625 + - 0.029830784881126345; f1_score = 0.8518945470921631 + - 0.0302014389693
65068; accuracy = 0.8524591924398625 +/- 0.029830784881126345
** 2-w2v-gru **
Training: precision = 0.9605378664916253 + /- 0.004551594616551951; recall = 0.9602110196832603 + /- 0.004651645803128308; f1_score = 0.9601789604723583 + /- 0.004683359
084519128; accuracy = 0.9602110196832603 +/- 0.004651645803128308
Test: precision = 0.8563507510025798 + - 0.03342641079145002; recall = 0.8514175257731958 + - 0.032567107034540084; f1_score = 0.8513426599557075 + - 0.03220000064051
147; accuracy = 0.8514175257731958 +/- 0.032567107034540084
```





RNN (W2V + LSTM y W2V + GRU)

TABLE III
RESULTADOS DE WORD2VEC + LSTM Y WORD2VEC + GRU

Modelo	Conjunto	Precisión	Recall	F1-Score	Accuracy
w2v + LSTM	Entrenamiento	0.9487 ± 0.0086	0.9483 ± 0.0089	0.9482 ± 0.0090	0.9483 ± 0.0089
	Prueba	0.8580 ± 0.0331	0.8525 ± 0.0298	0.8519 ± 0.0302	0.8525 ± 0.0298
w2v + GRU	Entrenamiento	0.9605 ± 0.0046	0.9602 ± 0.0047	0.9602 ± 0.0047	0.9602 ± 0.0047
	Prueba	0.8564 ± 0.0334	0.8514 ± 0.0326	0.8513 ± 0.0322	0.8514 ± 0.0326

METRICAS



$$R = \frac{TP}{TP + FN}$$

Precision (P)

$$P = \frac{TP}{TP + FP}$$

F1-Score

$$F1$$
-Score = $2 \times \frac{P \times R}{P + R}$

Útil en contextos desbalanceados.

Accuracy (A)

$$A = \frac{TP + TN}{TP + TN + FP + FN}$$

Engañosa en conjuntos de datos desequilibrados



REFERENCIAS

Dias Canedo, E., & Cordeiro Mendes, B. (2020). Software Requirements Classification Using Machine Learning Algorithms. *Entropy*, *22*(9), 1057. https://doi.org/10.3390/e22091057

Kaur, K., Kaur, P. The application of AI techniques in requirements classification: a systematic mapping. Artif Intell Rev 57, 57 (2024). https://doi.org/10.1007/s10462-023-10667-1

MUCHAS GRACIAS

Computer Science