Named Entity Recognition using BiLSTM and its variants

Harman Singh

Shubham Mittal

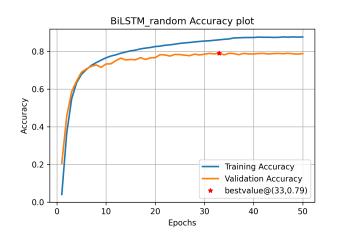
Simple BiLSTM results

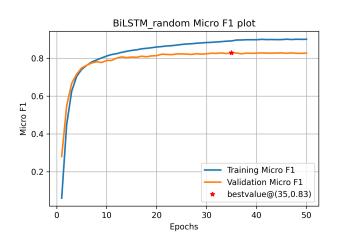
- BiLSTM with Random Word Embeddings

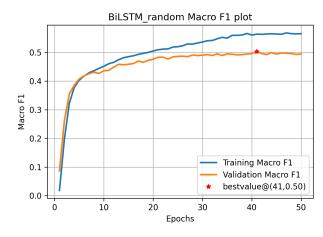
CONLL based final performance metrics (after training):

	Accuracy	Micro F1	Macro F1
Train	0.982	0.889	0.755
Validation	0.964	0.803	0.619
Test	0.964	0.804	0.614

Plots for performance statistics vs epochs:



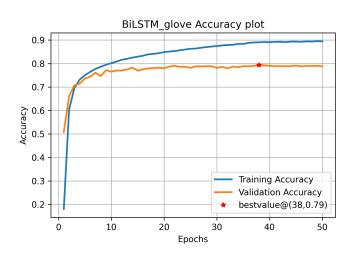


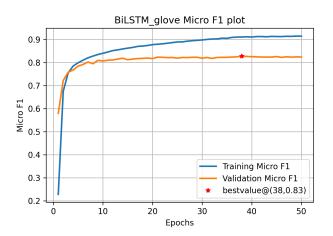


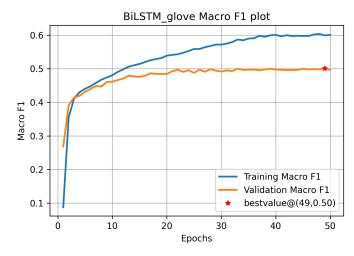
- BiLSTM with Pretrained (Glove) word embeddings CONLL based final performance metrics (after training):

	Accuracy	Micro F1	Macro F1
Train	0.986	0.909	0.823
Validation	0.961	0.793	0.620
Test	0.962	0.794	0.614

Plots for performance statistics vs epochs:



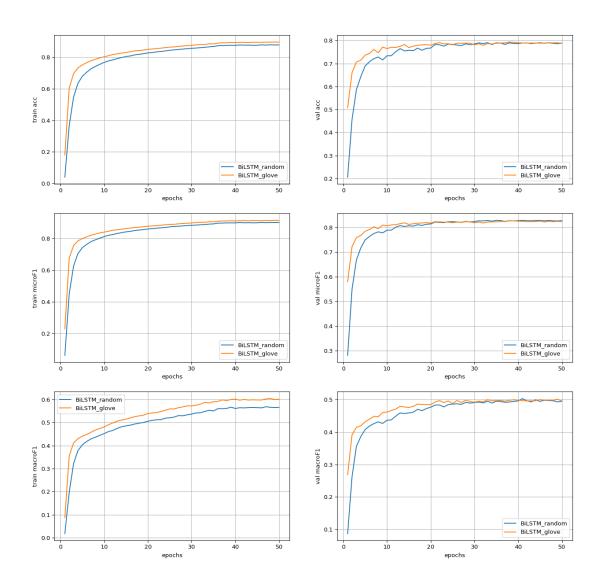




- Comparison of Simple BiLSTM with Random and Glove embeddings

(Following Plots, 3 rows respectively are for accuracy, microF1 and macroF1. Left column - Training, Right column - Validation)

(orange line - glove, blue line - random)



Comments

- We see that with glove embeddings the model trains faster than with random embeddings (ie
 with glove embeddings it takes less number of epochs for same performance). We conclude this
 because for all the plots, accuracy, microF1 and MacroF1, for both train and validation sets, the
 curve for BiLSTM with glove embeddings remains above that of random embeddings
- Faster training is expected because glove embeddings provide embeddings, which are similar for similar words, and this pretraining of the embeddings means that we do not have to learn the embedding now, we can just fine tune it during training. While in case of random embeddings all the embeddings also have to be learnt which takes more time.

• The final performance of both BiLSTM's are similar hence we can say that random embeddings are changed during training (learnt) to represent meaningful information from words just like glove embeddings.

Results using BiLSTM using character level features and pretrained embeddings

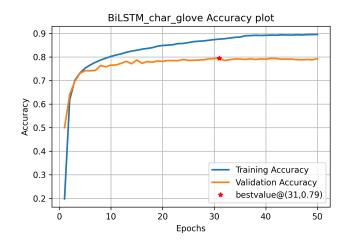
We use a separate BiLSTM for generating forward and backward character level embeddings of the Word which is concatenated with the word embeddings. Total embedding size now becomes 100+25+25 = 150

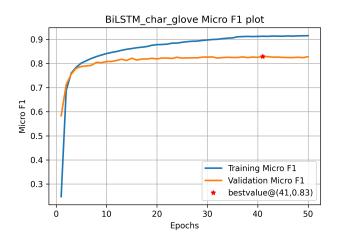
- BiLSTM with Character Level Embeddings + Pretrained (Glove) word embeddings (concatenated)

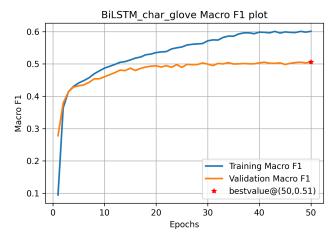
CONLL based final performance metrics (after training):

	Accuracy	Micro F1	Macro F1
Train	0.986	0.908	0.820
Validation	0.961	0.795	0.629
Test	0.962	0.795	0.626

Plots for performance statistics vs epochs:







- Comparison between BiLSTM (Char Level + Glove) model with Bilstm (Glove)

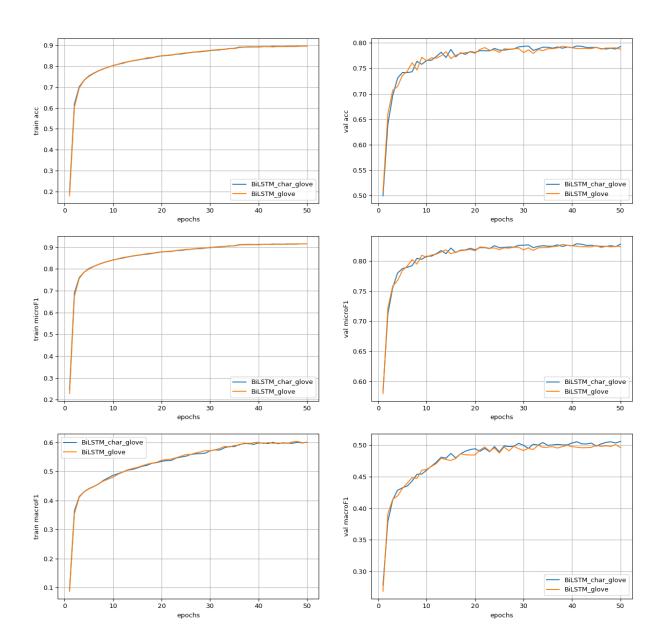
On the basis of Final Performance:

Model	Validation		Т	est
	MicroF1	MacroF1	MicroF1	MacroF1
BiLSTM (Glove embeds)	0.793	0.620	0.794	0.614
BiLSTM (Char Level + Glove embeds)	0.795	0.629	0.795	0.626

On the basis of learning curves:

(Following Plots, 3 rows respectively are for accuracy, microF1 and macroF1. Left column - Training, Right column - Validation)

(orange line - glove, blue line - char+glove)



Comments:

 For Validation and Test data, the BiLSTM with character and word embeddings perform better in terms of both micro and macro F1 score. This is expected since we are giving the model character level information of the words, hence this will help enhancing the embeddings of the

- words (giving more information) and would also be helpful to words which are not in the training set (out of vocabulary), to have better representation than the standard "<OOV>" tag during validation and test time.
- The training curves for both models are very similar, hence speed of learning for both the models
 is almost the same, ie the additional lstm required for getting the character level embeddings
 does not consume more time (this is due to fully vectorized implementation to get char level
 embeddings without looping over words).

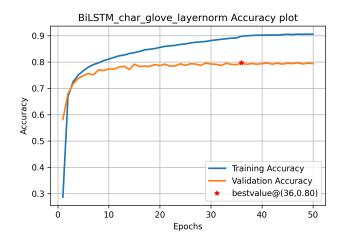
Results using BiLSTM with LayerNormalization, using character level features and pretrained embeddings

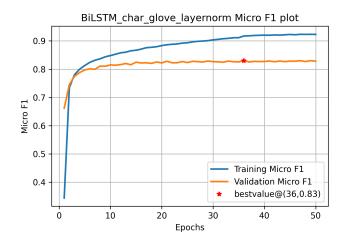
- Implementation details of LSTM with Layer Normalization:
 - 1. We replace nn.LSTM with our implementation of LSTM, which uses layer-normed LSTM Cell implementation.
 - 2. Inside the LSTM cell, since there are 5 non-linearities, thus the input to them is normalized.
 - 3. In total, three layer norm layers are used. Two are applied on the linear transformations : $W_{x2h}.x_t$ and $W_{h2h}.h_{t-1}$. Third layer norm layer is applied on c_t .
- BiLSTM with Layer Normalization (used Character Level Embeddings + Pretrained (Glove) word embeddings (concatenated))

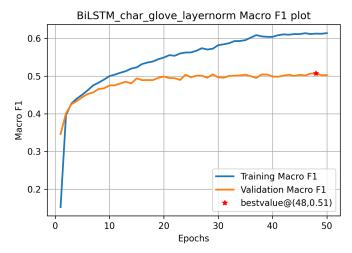
CONLL based final performance metrics (after training):

	Accuracy Micro F1		Macro F1
Train	0.989	0.923	0.851
Validation	0.963	0.799	0.625
Test	0.963	0.802	0.627

Plots for performance statistics vs epochs:







- Comparison between BiLSTM (Char Level + Glove) with and without Layer Normalization

On the basis of Final Performance:

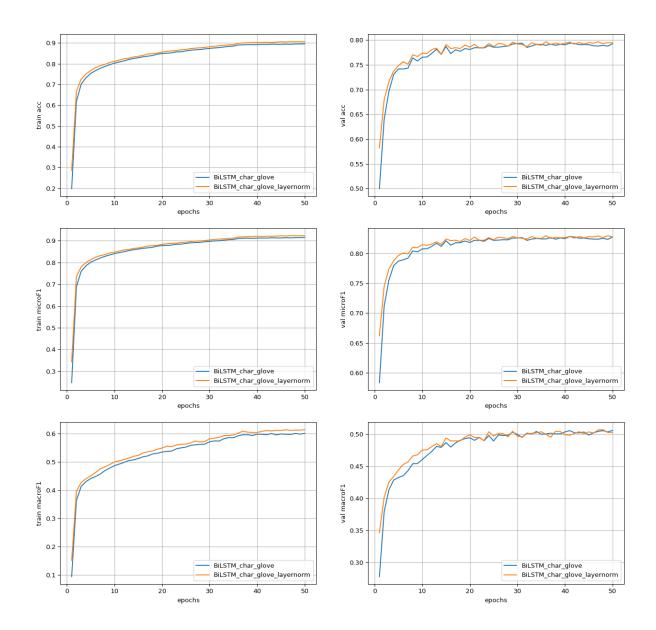
Model	Validation		Test	
	MicroF1	MacroF1	MicroF1	MacroF1
BiLSTM (Glove embeds)	0.793	0.620	0.794	0.614
BiLSTM (Char Level + Glove embeds)	0.795	0.629	0.795	0.626
Without Layer Norm				

BiLSTM (Char Level + Glove embeds)	0.799	0.625	0.802	0.627
With Layer Norm				

On the basis of learning curves:

(Following Plots, 3 rows respectively are for accuracy, microF1 and macroF1. Left column - Training, Right column - Validation)

(orange line - char+glove+layernorm, blue line - char+glove)



Comments:

- For Validation and Test data, the BiLSTM with Layer Normalization performs better in terms of Micro F1 score and similar in terms of macro F1 score on test data.
- In most of the curves above, normalized variant of the model, has its curve above the unnormalized. Hence speed of training with layer normalization is more that without it. This is expected because loss landscape with normalization becomes smoother and even (in terms of

gradient) in all directions which lets the model take larger gradient steps (in case of adam optimizer which we have used) hence faster training.

Linear chain CRF

Initialization of the CRF transition matrix:

- The appropriate initialization of the transition matrix would be to choose small random values for all the cells of the transition matrix **except the cells representing transition from stop state**, **or transition to start state**. These cells should be initialized using a very high negative value (like -10000, -20000) so that the exponent of that tends to 0 basically suggesting that these transitions are impossible(logically we cannot transition to start state or transition from stop state, these have to be beginning and end states respectively).
- Another intuition is that if the forbidden transitions take place then, the large negative value of the transition score would make the exponent in the numerator of the likelihood function nearly 0, which would cause the negative log likelihood to go to +inf. To avoid this, these transitions would never take place.

Loss function for CRF:

- The negative of the log likelihood function described in the paper (Lample et.al.) was used as our loss function.

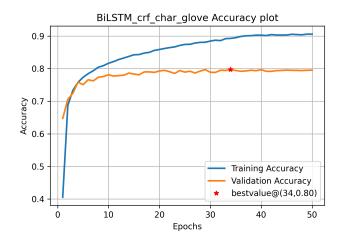
BiLSTM + CRF layer results

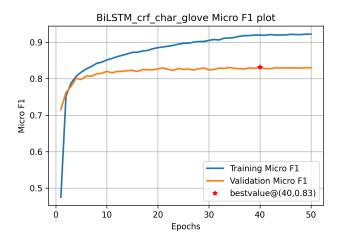
We experimented by first using out BiLSTM + CRF model with character level features and pretrained word embeddings which gave us a performance boost. After this we also tried out adding layer norm to the above architecture (using layer normalized BiLSTM) which further improved our performance. Results for both experiments are shown below

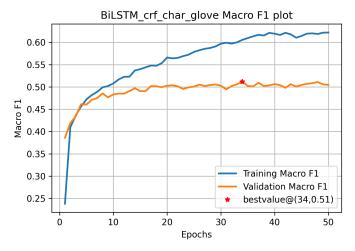
- BiLSTM (Char level features + pretrained embeddings) + CRF CONLL based final performance metrics (after training):

	Accuracy	Micro F1	Macro F1	
Train	0.988	0.930	0.890	
Validation	0.962	0.814	0.643	
Test	0.962	0.817	0.634	

Plots for performance statistics vs epochs:



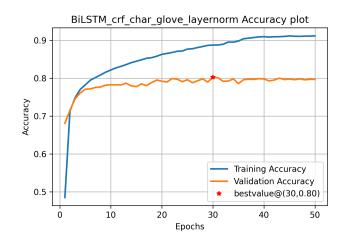


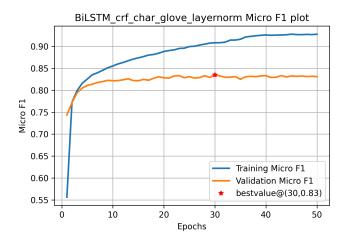


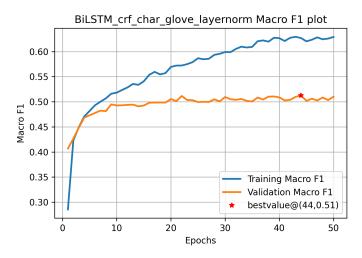
BiLSTM with Layer Normalization (Char level features + pretrained embeddings)+ CRF
 CONLL based final performance metrics (after training):

	Accuracy	Micro F1	Macro F1	
Train	0.990	0.941	0.907	
Validation	0.964	0.820	0.649	
Test	0.964	0.820	0.635	

Plots for performance statistics vs epochs:







- Comparison between BiLSTM with CRF with other variants

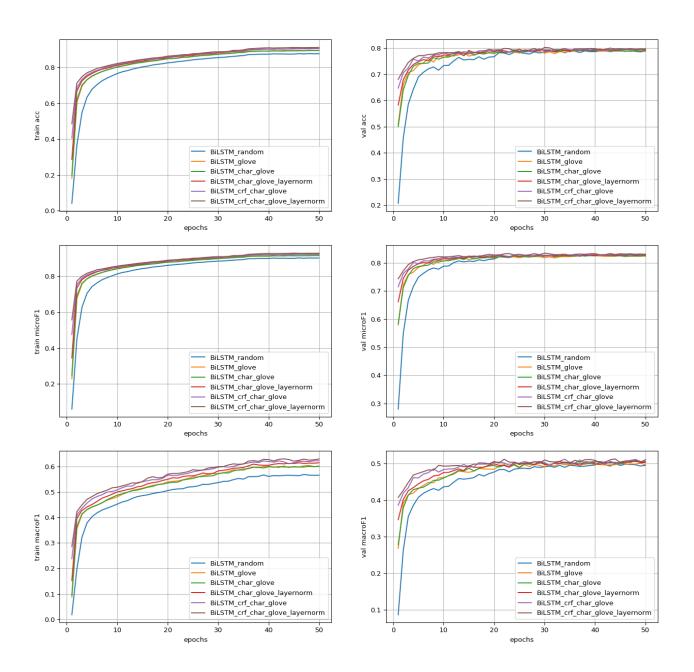
On the basis of Final Performance:

Model	Validation		Test	
	MicroF1	MacroF1	MicroF1	MacroF1
BiLSTM (random embeddings)	0.803	0.619	0.804	0.614
BiLSTM (Glove embeddings)	0.793	0.620	0.794	0.614
BiLSTM (Glove + char embeddings)	0.795	0.629	0.795	0.626

BiLSTM with Layernorm (Glove + char embeddings)	0.799	0.625	0.802	0.627
BiLSTM with CRF (Glove + char embeddings)	0.814	0.643	0.817	0.634
BiLSTM with LayerNorm + CRF (Glove + char embeddings)	0.820	0.649	0.820	0.635

On the basis of learning curves:

(Following Plots, 3 rows respectively are for accuracy, microF1 and macroF1. Left column - Training, Right column - Validation)



Comments:

• The BiLSTM with CRF layer implemented on top of it, gives the best performance among all other variants for NER tagging. The gain in performance is also the highest, as compared to any other performance enhancer (layernorm/char embeddings/glove embeddings).

- This can be attributed to CRF being able to capture relationship between words using the transition scores internally, which can be thought of as a regularizer, which imposes (and learns) certain priors on the output sentences (whether one word can follow the other, etc)
- We see a gradual increase in performance as we increase the complexity of the model and introduce new performance enhancing measures. Glove embeddings proved to be better than random embeddings in terms of learning curves (faster learning). Including character level features improved performance and gave the model better representation of the tokens. This was improved upon by the normalization by the layernorm. Finally the CRF model with layer norm proved to be the best for ner tagging in our case.
- Referring to the curves above, we see that Bilstm with layernorm, crf and using char and glove
 embeddings learns the fastest among all models in general. The layernorm has its advantage in
 speed of training as described in the layernorm section of this document, and crf introduces
 extra constraints and learns the relationship between words in a sentence which may have
 helped us achieve faster training.
- Without layer norm, Bilstm with crf and using char and glove has slightly less speed of training and has the curve below that of the layernorm variant.
- The general trend of the plots is that the speed of training increases with increase in complexity
 of the model, and the complexity can be introduced by adding layernorm, crf, glove embeddings,
 char level embeddings etc. Best model is the combination of all, both in terms of speed and final
 accuracy.

Appendix

2.1.2

- Classification Report for Simple BiLSTM with Random Embeddings (Train, Validation and Test data respectively)

PERFORMAN	NCE ON Tra	ain DATA			
MicroF1 = 0.8891281071185972					
Accuracy	= 0.9821	8883935540	009		
	Class	ification	Report-		
	pre	cision	recall	f1-score	support
	art	0.673	0.341	0.453	296
	eve	0.543	0.478	0.508	226
	geo	0.886	0.937	0.911	29240
	gpe	0.968	0.942	0.955	12058
	nat	0.714	0.564	0.630	133
	org	0.805	0.777	0.791	15803
	per	0.879	0.879	0.879	13121
	tim	0.922	0.911	0.917	15767
micro	avg	0.887	0.891	0.889	86644
macro	avg	0.799	0.729	0.755	86644
weighted	avg	0.886	0.891	0.888	86644

PERFORMANCE ON Validation DATA MicroF1 = 0.8034243979743Accuracy = 0.9635724503487508--Classification Report-precision recall f1-score support art 0.265 0.086 0.129 105 0.297 0.380 0.244 78 eve 0.823 0.866 0.844 9724 geo 0.908 0.922 0.936 4210 gpe 0.440 0.518 nat 0.629 50 0.623 0.629 org 0.635 5187 0.744 0.750 per 0.757 4457 tim 0.881 0.853 0.867 5254 micro avg 0.804 0.802 0.803 29065 macro avq 0.595 0.619 0.663 29065 weighted avg 0.802 0.803 0.802 29065

PERFORMANCE ON Test DATA						
MicroF1 =	= 0.803867	7876091049	91			
Accuracy	= 0.96363	361616318	73			
	Class:	ification	Report-			
	pred	cision	recall	f1-score	support	
	art	0.280	0.069	0.110	102	
	eve	0.378	0.322	0.348	87	
	geo	0.831	0.871	0.851	9912	
	gpe	0.928	0.907	0.918	4168	
	nat	0.571	0.364	0.444	55	
	org	0.634	0.623	0.628	5205	
	per	0.758	0.753	0.756	4406	
	tim	0.868	0.844	0.856	5275	
micro	avg	0.804	0.804	0.804	29210	
macro	avg	0.656	0.594	0.614	29210	
weighted	avg	0.802	0.804	0.802	29210	

Classification Report for Simple BiLSTM with Glove

(Train, Validation and Test data respectively)

PERFORMANCE ON Train DATA					
MicroF1 =	= 0.90925	935516540	92		
Accuracy	= 0.9859	880455904	748		
	Class	ification	Report-		-
	pre	cision	recall	f1-score	support
	art	0.782	0.632	0.699	296
	eve	0.716	0.681	0.698	226
	geo	0.901	0.949	0.925	29240
	gpe	0.970	0.952	0.961	12058
	nat	0.728	0.564	0.636	133
	org	0.848	0.809	0.828	15803
	per	0.908	0.902	0.905	13121
	tim	0.930	0.935	0.933	15767
micro	avg	0.907	0.912	0.909	86644
macro	avg	0.848	0.803	0.823	86644
weighted	avg	0.906	0.912	0.909	86644

PERFORMANCE ON Validation DATA

MicroF1 = 0.7928936234766631

Accuracy = 0.9614248697959983

----- Report-----

Classification		Report			
	pre	cision	recall	f1-score	support
	art eve	0.500 0.400	0.152 0.282	0.234 0.331	105 78
	geo	0.807	0.872	0.838	9724
	gpe	0.934	0.914	0.924	4210
	nat	0.514	0.380	0.437	50
	org	0.583	0.638	0.609	5187
	per	0.737	0.735	0.736	4457
	tim	0.844	0.866	0.855	5254
micro	avg	0.777	0.809	0.793	29065
macro	avg	0.665	0.605	0.620	29065
weighted	avg	0.779	0.809	0.793	29065

	NCE ON Te	st DATA 338436230	58		
		140577955			
_					_
		cision	_	f1-score	
	Pre	CISION	recarr	II-SCOLE	support
	art	0.480	0.118	0.189	102
	eve	0.341	0.322	0.331	87
	geo	0.818	0.875	0.846	9912
	gpe	0.931	0.916	0.923	4168
	nat	0.621	0.327	0.429	55
	org	0.585	0.634	0.609	5205
	per	0.735	0.743	0.739	4406
	tim	0.836	0.860	0.848	5275
micro	avg	0.779	0.810	0.794	29210
macro	avg	0.668	0.599	0.614	29210
weighted	avg	0.780	0.810	0.794	29210

2.1.3

- Classification Report for Simple BiLSTM with Character + Word embeddings

(Train, Validation and Test data respectively)

PERFORMAN	NCE ON Tra	ain DATA			
	= 0.90838		3.8		
	= 0.98600				
-					
			-		
	pre	cision	recall	f1-score	support
	art	0.738	0.581	0.650	296
	eve	0.738	0.673	0.704	226
	geo	0.899	0.952	0.925	29240
	gpe	0.972	0.949	0.960	12058
	nat	0.741	0.602	0.664	133
	org	0.850	0.816	0.832	15803
	per	0.905	0.896	0.900	13121
	tim	0.923	0.934	0.928	15767
micro	avg	0.904	0.912	0.908	86644
macro	avg	0.846	0.800	0.820	86644
weighted	avg	0.904	0.912	0.908	86644

PERFORMANCE ON Validation DATA MicroF1 = 0.7951207958313595

Accuracy = 0.9612918011214732 -----Classification Report-----

Classification		Report-		-
pred	ision	recall	f1-score	support
art	0.370	0.162	0.225	105
eve	0.469	0.295	0.362	78
geo	0.809	0.875	0.841	9724
gpe	0.938	0.910	0.924	4210
nat	0.512	0.420	0.462	50
org	0.563	0.640	0.599	5187
per	0.774	0.729	0.751	4457
tim	0.870	0.862	0.866	5254
avg	0.782	0.808	0.795	29065
avg	0.663	0.612	0.629	29065
avg	0.786	0.808	0.796	29065
	pred eve geo geo at org er im	precision ort 0.370 eve 0.469 geo 0.809 gpe 0.938 oat 0.512 org 0.563 oer 0.774 eim 0.870 ovg 0.782 ovg 0.663	precision recall ort 0.370 0.162 eve 0.469 0.295 geo 0.809 0.875 gpe 0.938 0.910 eat 0.512 0.420 erg 0.563 0.640 er 0.774 0.729 eim 0.870 0.862 evg 0.782 0.808 evg 0.782 0.808 evg 0.663 0.612	art 0.370 0.162 0.225 eve 0.469 0.295 0.362 geo 0.809 0.875 0.841 gpe 0.938 0.910 0.924 eat 0.512 0.420 0.462 erg 0.563 0.640 0.599 er 0.774 0.729 0.751 eim 0.870 0.862 0.866 evg 0.782 0.808 0.795 evg 0.663 0.612 0.629

PERFORMANCE ON Test DATA MicroF1 = 0.7945924132364811 Accuracy = 0.9616400205909911						
_						
		cision	-	f1-score		
	art	0.308	0.118	0.170	102	
	eve	0.444	0.368	0.403	87	
	geo	0.818	0.880	0.848	9912	
	gpe	0.931	0.911	0.921	4168	
	nat	0.600	0.382	0.467	55	
	org	0.564	0.636	0.598	5205	
	per	0.766	0.734	0.749	4406	
	tim	0.852	0.853	0.852	5275	
micro	avg	0.781	0.809	0.795	29210	
macro	avg	0.660	0.610	0.626	29210	
weighted	avg	0.784	0.809	0.795	29210	

2.1.4

- Classification Report for BiLSTM with Layer Normalization using Character + Word embeddings (Train, Validation and Test data respectively)

PERFORMANCE ON Train DATA MicroF1 = 0.9233053568152632 Accuracy = 0.9887547920269522

Classification	Report
----------------	--------

pre	ecision	recall	f1-score	support
art	0.779	0.713	0.744	296
eve	0.683	0.752	0.716	226
geo	0.915	0.958	0.936	29240
gpe	0.972	0.955	0.964	12058
nat	0.673	0.789	0.727	133
org	0.875	0.848	0.861	15803
per	0.918	0.917	0.917	13121
tim	0.931	0.955	0.943	15767
avg	0.917	0.929	0.923	86644
avg	0.843	0.861	0.851	86644
avg	0.917	0.929	0.923	86644
	rt eve geo gpe aat org er im	eve 0.683 geo 0.915 gpe 0.972 nat 0.673 org 0.875 oer 0.918 sim 0.931 ovg 0.917 ovg 0.843	ort 0.779 0.713 eve 0.683 0.752 geo 0.915 0.958 gpe 0.972 0.955 eat 0.673 0.789 erg 0.875 0.848 er 0.918 0.917 eim 0.931 0.955 evg 0.917 0.929 evg 0.843 0.861	art 0.779 0.713 0.744 eve 0.683 0.752 0.716 geo 0.915 0.958 0.936 gpe 0.972 0.955 0.964 eat 0.673 0.789 0.727 erg 0.875 0.848 0.861 er 0.918 0.917 0.917 eim 0.931 0.955 0.943 evg 0.917 0.929 0.923 evg 0.843 0.861 0.851

PERFORMANCE ON Validation DATA MicroF1 = 0.7989299742652038 Accuracy = 0.9626003097543034

-----Classification Report-----

CIASSILICACION	Kepor c			
precision	recall	f1-score	support	
0.385	0.190	0.255	105	
0.289	0.282	0.286	78	
0.810	0.874	0.841	9724	
0.940	0.912	0.926	4210	
0.460	0.460	0.460	50	
0.597	0.643	0.620	5187	
0.767	0.736	0.752	4457	
0.850	0.870	0.860	5254	
0.786	0.812	0.799	29065	
0.637	0.621	0.625	29065	
0.788	0.812	0.799	29065	
	precision 0.385 0.289 0.810 0.940 0.460 0.597 0.767 0.850 0.786 0.637	precision recall 0.385 0.190 0.289 0.282 0.810 0.874 0.940 0.912 0.460 0.460 0.597 0.643 0.767 0.736 0.850 0.870 0.786 0.812 0.637 0.621	0.385 0.190 0.255 0.289 0.282 0.286 0.810 0.874 0.841 0.940 0.912 0.926 0.460 0.460 0.460 0.597 0.643 0.620 0.767 0.736 0.752 0.850 0.870 0.860 0.786 0.812 0.799 0.637 0.621 0.625	

PERFORMANCE ON Test DATA MicroF1 = 0.801542399137873 Accuracy = 0.9631102766081157

-----Classification Report-----

		precision	recall	f1-score	support
	art	0.245	0.118	0.159	102
	eve	0.361	0.402	0.380	87
	geo	0.822	0.881	0.850	9912
	gpe	0.936	0.910	0.923	4168
	nat	0.535	0.418	0.469	55
	org	0.598	0.645	0.621	5205
	per	0.764	0.746	0.755	4406
	tim	0.845	0.866	0.855	5275
micro	avg	0.789	0.815	0.802	29210
macro	avg	0.638	0.623	0.627	29210
weighted	avg	0.790	0.815	0.802	29210

 Classification Report for BiLSTM + CRF with Character + Word embeddings (Train, Validation and Test data respectively)

2.2

PERFORMANCE ON Train DATA MicroF1 = 0.93000374866634Accuracy = 0.9880861513954801

-----Classification Report-----

		precision	recall	f1-score	support
	art	0.912	0.767	0.833	296
	eve	0.846	0.827	0.837	226
	geo	0.923	0.958	0.940	29240
	gpe	0.975	0.961	0.968	12058
	nat	0.775	0.827	0.800	133
	org	0.887	0.850	0.868	15803
	per	0.934	0.920	0.927	13121
	tim	0.947	0.951	0.949	15767
micro	avg	0.929	0.931	0.930	86644
macro	avg	0.900	0.883	0.890	86644
weighted	avg	0.929	0.931	0.930	86644

PERFORMANCE ON Validation DATA

MicroF1 = 0.8143543471148381

Accuracy = 0.9615875092870846

Classification		Report			
	pre	cision	recall	f1-score	support
	art	0.500	0.171	0.255	105
	eve	0.423	0.282	0.338	78
	geo	0.828	0.870	0.848	9724
	gpe	0.939	0.921	0.930	4210
	nat	0.524	0.440	0.478	50
	org	0.645	0.656	0.650	5187
	per	0.803	0.740	0.770	4457
	tim	0.884	0.866	0.875	5254
micro	avg	0.815	0.814	0.814	29065
macro	avg	0.693	0.618	0.643	29065
weighted	avg	0.815	0.814	0.813	29065

PERFORMANCE ON Test DATA MicroF1 = 0.816718054128126 Accuracy = 0.9620807270545624						
	Class	ification	Report-			
		cision	-	fl-score	support	
	art	0.414	0.118	0.183	102	
	eve	0.417	0.345	0.377	87	
	geo	0.838	0.877	0.857	9912	
	gpe	0.931	0.917	0.924	4168	
	nat	0.478	0.400	0.436	55	
	org	0.651	0.656	0.654	5205	
	per	0.801	0.748	0.774	4406	
	tim	0.879	0.862	0.870	5275	
micro	avg	0.817	0.816	0.817	29210	
macro	avg	0.676	0.615	0.634	29210	
weighted	avg	0.816	0.816	0.816	29210	

 Classification Report for BiLSTM + CRF with Character + Word embeddings AND Layer Norm (Train, Validation and Test data respectively)

PERFORMANCE ON Train DATA
MicroF1 = 0.9408832687736344
Accuracy = 0.9901621330619439

Classification	Report
----------------	--------

		precision	recall	f1-score	support	
	art	0.900	0.818	0.857	296	
	eve	0.858	0.832	0.845	226	
	geo	0.933	0.968	0.950	29240	
	gpe	0.977	0.967	0.972	12058	
	nat	0.800	0.902	0.848	133	
	org	0.919	0.869	0.893	15803	
	per	0.934	0.937	0.936	13121	
	tim	0.944	0.964	0.954	15767	
micro	avg	0.938	0.943	0.941	86644	
macro	avg	0.908	0.907	0.907	86644	
weighted	avg	0.938	0.943	0.941	86644	

PERFORMANCE ON Validation DATA MicroF1 = 0.8200622621930128 Accuracy = 0.964174955736184

-----Classification Report-----

	•	TODDITION OF OIL			
		precision	recall	f1-score	support
	art	0.346	0.171	0.229	105
	eve	0.450	0.346	0.391	78
	geo	0.834	0.868	0.851	9724
	gpe	0.931	0.923	0.927	4210
	nat	0.480	0.480	0.480	50
	org	0.714	0.648	0.679	5187
	per	0.784	0.754	0.769	4457
	tim	0.865	0.873	0.869	5254
micro macro		0.824 0.676	0.816 0.633	0.820 0.649	29065 29065
weighted	avg	0.821	0.816	0.818	29065

PERFORMANCE ON Test DATA MicroF1 = 0.8200697390796503 Accuracy = 0.9640398339388417

-----Classification Report-----

	orapprization Report				
		precision	recall	f1-score	support
	art	0.233	0.098	0.138	102
	eve	0.397	0.356	0.376	87
	geo	0.840	0.871	0.855	9912
	gpe	0.924	0.924	0.924	4168
	nat	0.464	0.473	0.468	55
	org	0.705	0.644	0.673	5205
	per	0.784	0.767	0.775	4406
	tim	0.863	0.871	0.867	5275
micro	avg	0.823	0.817	0.820	29210
macro	avg	0.651	0.625	0.635	29210
weighted	avg	0.819	0.817	0.818	29210