Homework 2: Aspect-Based Sentiment Analysis

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1 Introduction

Aspect-based sentiment analysis (ABSA) tackles the problem of finding both aspects in a given sentence, and the polarities associated with those aspects. For example, given the sentence "I love their pasta but I hate their Ananas Pizza", the task is to first extract the two aspects "pasta" and "Ananas Pizza", and to then predict their associated polarities, in this case respectively "positive" and "negative".

In this paper, I propose an end-to-end approach to attack this task, exploiting the combination of both context-independent (GloVe) and context-dependent (BERT) word embeddings, multihead attention layers, and the use of a BiLSTM layer, reaching satisfying results on the provided development dataset (macro f1 score of 0.544 on the Restaurants + Laptops development set).

2 Problem formulation

All the model variations proposed in this paper tackle the ABSA problem in an end-to-end fashion, meaning that both tasks (i.e., aspect sentiment extraction and aspect sentiment polarity evaluation) are solved simultaneously. To achieve this, the two-sided problem has been formulated as a sequence labeling task.

To that end, this is the general pipeline followed: during the preprocessing, each token of each sentence is tagged using either an IOB (i.e., Inside, Outside, Beginning) or a BIOES (i.e., Beginning, Inside, Outside, Ending, Single) tagging schema, used on top of the four polarities appearing in the datasets (example of the two tagging schemas in fig. 1). Depending on the adopted tagging schema, the model is then trained to extract the right label from a set of either $4 \cdot 2 + 1 = 9$ (for IOB) or $4 \cdot 4 + 1 = 17$ (for BIOES) possible classes. Finally, the model output is translated back into its original form, where the tokens classified as "O" are not considered and the aspect terms are merged together according to their tags (e.g., $\{$"Ananas" = B-negative, "Pizza" = I-negative$\} \rightarrow \{$"Ananas Pizza" = negative$\}$).

3 Models

In this section, I will present all the modules that compose the proposed final model, starting by introducing the structure of the baseline network. Then, at each step, I will introduce the very next module used, describing its main functionalities and analyzing the boost in terms of performance when added to the network.

To evaluate the performance of the following models, I will use their macro f1 score on the combined task of aspect term extraction and evaluation.

Moreover, IOB has been selected as the preferred tagging schema, and all the following model performances are computed using that. Finally, all models have been trained using AdamW as optimizer.

3.1 M0: Baseline

The first model used to solve the ABSA task is a very simple network, composed by an embedding layer to encode the tokens of the input sentences, followed by a one-on-one linear layer (i.e., input features = output features) with ReLU activation, two stacked BiLSTM layers and a prediction block, composed by a linear layer and a softmax activation (network architecture in fig. 2). Additionally, I replaced the randomly initialized word embeddings in the embedding layer with the pre-trained word vectors of GloVe (Pennington et al., 2014).

In this first model variation, no contextual information is considered in the embedding phase, since the word embeddings provided by GloVe, being context-free, will produce the same vector representation regardless of the context. Nevertheless, the BiLSTM layers partially make up for this, encoding both the left-to-right and the right-to-left context for each word of a sentence.

This very simple architecture (let's call it M0) is still able to achieve decent results in terms of f1 score, reaching a maximum of 0.381 in terms of macro f1 score (see figs. 4, 6, 8 respectively for the loss plots, f1 extraction and f1 extraction + evaluation plots on the train. and dev. datasets).

3.2 M1: BERT Embedder

To add contextual information to my model, I decided to use BERT (Bidirectional Encoder Representations Transformers) (Devlin et al., 2018). BERT is a language representation model which uses bidirectional transformers to pre-train on very large corpora over different pre-training tasks. Then, the pre-trained BERT model can be fine-tuned to be used on other tasks. In my case, I decided to use BERT as an embedding layer, as suggested by (Li et al., 2019). Differently from the traditional GloVe based embedding layer, which, as previously mentioned, provides only context-independent representation for each token, using BERT as an embedding layer provides context-dependant information about each token in a sentence.

To get the most out of BERT, I followed one of the approaches proposed by (Ács et al., 2021) as the pooling strategy. In particular, the approach can be summarized in two steps: first, the BERT embeddings for the subwords of each token are computed: this is achieved by averaging the last 3 hidden layers of BERT. Then, the weighted average of the subwords embeddings are computed, based on the BPE length of each token.

This process can be carried out in two ways: keeping the BERT parameters frozen, or allowing them to change and finetuning them during the training process. These two possible choices are the basis of a trade off between two possible scenarios: on the one hand, keeping the BERT weights frozen, we have a much easier time when training our model, in terms of both training time and flexibility in the choice of the hyperparameters. On the other, learning also the parameters for the BERT model allows to potentially achieve much better results.

Once the BERT embeddings have been computed, similarly to the GloVe embeddings, they are too passed into a linear layer with a ReLU activation, and subsequently concatenated with the GloVe pretrained embeddings. The rest of the network is the same. Adding context-dependent information with BERT and keeping its parameters frozen (let's call this model M1), the model reaches 0.466 macro f1 score on the dev set.

3.3 M2: Finetuning BERT

As already discussed, there is a big trade-off between training feasibility and performances. Exploiting the general representation given by BERT for such a fine-grained task as aspect based sentiment analysis is far from ideal, and therefore it just makes sense to fine-tune the BERT parameters. In order to do so, I noticed that the value for the optimizer learning rate really made a difference when fine-tuning the BERT embedder. Once a good value for that was found, I was able to reach 0.497 macro f1 score on the development set, just by not freezing the BERT parameters.

3.4 M3: Self-Attention

Self-attention is an attention mechanism relating different positions of a single sequence, in order to compute a new representation of the same sequence. It has been made popular by (Vaswani et al., 2017), and, intuitively, it makes it possible for the network to focus on relevant parts of a sentence. The attention scores are computed as follows:

$$\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V. \quad (1)$$

To attend different parts of a sentence, multiple attention heads can be computed and then concatenated. The resulting vector can be then linearly transformed into the expected dimension. This process is known as Multi-head Attention.

For my use case, I used Multi-head Attention as a feature extractor on both the GloVe embeddings and on the BERT embeddings, respectively using 12 and 24 heads. Then, as in the previous versions, I concatenated the two resulting embeddings, passed the result to the stacked BiLSTM layers, and finally to the prediction block.

This was the trick that made me reach the best results, achieving 0.544 macro f1 score on the development set. Therefore, this is the final proposed model for this homework (see fig. 3 for the model architecture, figs. 5, 7, 9 respectively for the loss plots, f1 extraction and f1 extraction + evaluation plots on the train. and dev. datasets).

4 Honorable mentions

In this section I'll briefly talk about two techniques that I tried, for which I had good expectations, but that, eventually, didn't make the cut.

4.1 M4: Conditional Random Field

Conditional Random Fields (CRF) (Lafferty et al., 2001) are very often used with success in sequence labeling tasks such as named entity recognition, as they model the likelihood of a given sequence, implementing dependencies between the predictions. For this reason, it seemed like a natural choice to adopt this approach in my use case. Unfortunately, this wasn't the case for the ABSA task, as, using CRF, the model performance has dropped to 0.493. I suspect that the reason behind this is that the embeddings computed with BERT provide enough information for a linear layer to work just better. In fact, removing the BERT embeddings and relying only on context-free embeddings given by GloVe, the CRF starts to shine, increasing the performances of the baseline model from 0.381 to 0.391.

4.2 M5: POS embeddings

In theory, part-of-speech tags should be an important tool, specifically in the aspect term extraction part. In fact, most of the aspect terms are represented by nouns, and therefore identifying the part of speech should at least work as a first selection, to rule out words that are very unlikely to be aspect terms. In practice, this didn't turn out to be true. I believe that there are several reasons why this is the case. First of all, the dataset doesn't provide a gold label for the POS tags of the tokens, and therefore, we must produce our own POS tags using a pretrained model. This means that we are injecting in our data a new potential source of errors, since the non-manually tagged data could be wrong in the first place.

Additionally, the aspect extraction task isn't that hard, in fact all models, even the baseline one, behave quite well on that task (see fig. 10).

For these reasons, embedding the POS tags and concatenating that to the other word representations made the performances drop to 0.509.

5 Conclusion

In this paper I have analyzed the performance of various models. In the end, I believe I have reached satisfactory results. Moreover, I think that the use of an end-to-end model for this task can be very beneficial for its simplicity, as it really needs very basic preprocessing on the text to be set up, and the output can be postprocessed trivially.

An ablation study is proposed in the final section. Specifically, see table 2 for the hyperparameters of the proposed model, table 5 for the performances of all the models, table 6 for the comparison between the proposed model using IOB vs BIOES, figs. 10 and 11 for the f1 score in terms of extraction and extraction + evaluation for all the models, and figs. 14 and 15 for the confusion matrices of the baseline and of the proposed model.

6 Extra

In this section I will talk about the additional optional task proposed, namely the combination of aspect category identification and aspect category polarity classification. For example, given the sentence "Prices are higher to dine in and their chicken tikka marsala is quite good", the task is to identify the two categories "food" and "price", and to then predict their associated polarities, in this case respectively "positive" and "negative".

The model proposed for this task directly inherits from the model used to tackle the previous tasks, and the only modification is made on the classification head, as this can no more be considered a sequence labeling task. Instead, the model has to make five independet predictions for a given sentence, one for each category ("anecdotes/miscellaneous", "price", "food", "ambience", "service"). Each prediction will span across 5 possible classes, which are the 4 traditional polarities ("positive", "negative", "neutral", "conflict") and one additional non-polarity "O", representing the fact that the input sentence does not have the selected category between its aspect categories.

This way, this problem too can be approached in an end-to-end fashion, without modifying too much the initial structure proposed. Using this approach, I am able to reach satisfactory results also in this additional task, reaching 0.576 macro f1 score on the task of category extraction + polarity evaluation on the development set (see figs. 16, 17, 18 for the loss, macro f1 extr., macro f1 extr. + eval. plots).

One final consideration can be made on this additional task. I think that the the connection between the two tasks could be exploited: for instance, an attempt could be made to use the predictions of the first model as input of the second model.

7 Figures and tables

All figures and tables have been intentionally placed at the end of the document, in this section, so that they don't affect the maximum limit of three pages for the text.

Sentiment	Train	Dev
positive	2605	546
negative	1364	307
neutral	877	216
conflict	111	25

Table 1: Polarities support for aspect terms (task A+B) in the training and development set (i.e., Restaurants + Laptops).

Hyperparameters	Value
Tagging schema	IOB
Vocabularies min. freq.	2
Batch size	16
Loss function	Cross Entropy
Optimizer	AdamW
Epochs	81
Learning rate	2e-5
Weight decay	0.0
Dropout rate	0.5
Dropout on attention	0.1
GloVe embeddings size	300
BERT embeddings	768 (bert-base-cased)
BiLSTM layers	2
BiLSTM hidden dim.	300
Activation functions	ReLU

Table 2: Hyperparameters for the proposed model (task A+B).

Category	Train	Dev
anecdotes/miscellaneous	941	191
price	268	53
food	1008	224
ambience	355	76
service	478	119

Table 3: Categories support (task C+D) in the training and development set (i.e., Restaurants).

Sentiment	Train	Dev
positive	1803	376
negative	672	167
neutral	411	89
conflict	164	31

Table 4: Polarities support for categories (task C+D) in the training and development set (i.e., Restaurants).

Model	F1 Extr.	F1 Eval.
M0 = Baseline	0.715	0.381
M1 = M0 + BERT$_{freeze}$	0.805	0.466
M2 = M0 + BERT$_{finetune}$	0.801	0.497
M3 = M2 + ATT	**0.819**	**0.544**
M4 = M3 + CRF	0.813	0.493
M5 = M3 + POS	0.798	0.509

Table 5: Task A+B: Ablation study, performances are computed on the development set (Restaurants + Laptops). For each variation, it has been selected the model with the highest f1 evaluation score on the validation set. Metric "F1 Eval." is the joint task of aspect term extraction and evaluation.

Model	F1 Extr.	F1 Eval.
M3$_{\mathrm{IOB}}$	**0.819**	**0.544**
M3$_{\mathrm{BIOES}}$	0.812	0.490

Table 6: Task A+B: Proposed model top performance comparison using two tagging schemas: IOB (i.e., Inside-Outside-Beginning), and BIOES (i.e., beginning, inside, outside, end, single).

	I	love	their	pasta	but	I	hate	their	Ananas	Pizza
-				positive					negative	
IOB	O	O	O	B-pos	O	O	O	O	B-neg	I-neg
BIOES	O	O	O	S-pos	O	O	O	O	B-neg	E-neg

Figure 1: IOB and BIOES tagging schemas example.

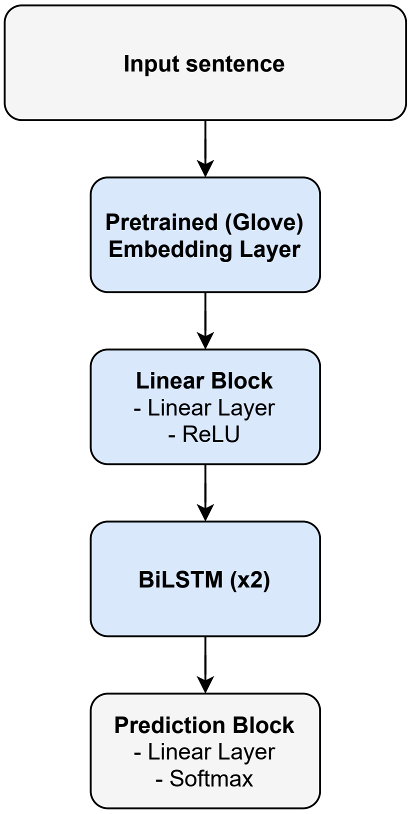

Figure 2: Baseline model (M0) architecture. There is a dropout layer after the GloVe embedding layer, and after the BiLSTM layer.

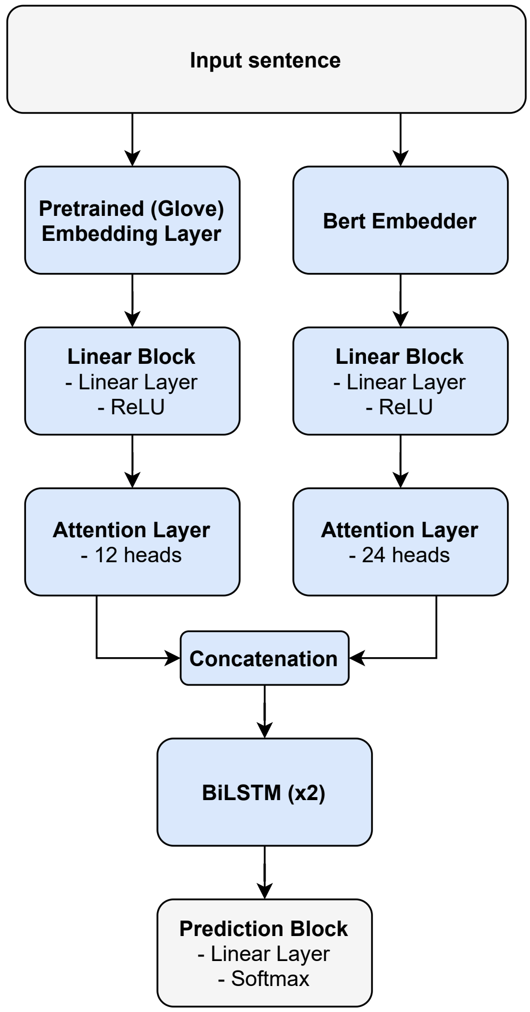

Figure 3: Final model (M3) architecture. There are dropouts after the GloVe embedding layer, the BERT embedding layer, after both attention layers, and after the BiLSTM layer.

Figure 4: Task A+B: Baseline (M0) loss on the training and development set.

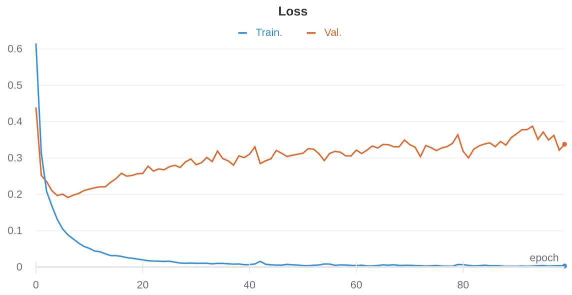

Figure 5: Task A+B: Final model (M3) loss on the training and development set. Looking at these plots and the metric ones it becomes clear that the loss cannot be the metric to be monitored (the model seems to converge after 10 epochs, while the f1 score continues to increase even after 20-30 epochs).

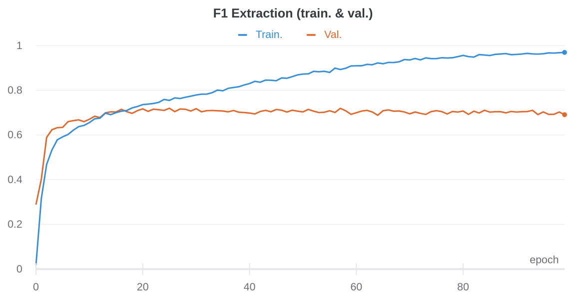

Figure 6: Task A+B: Baseline (M0) macro f1 extraction score on the training and development set.

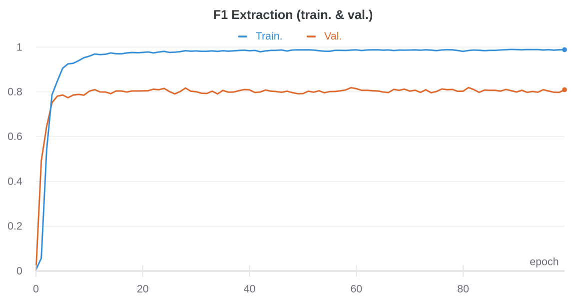

Figure 7: Task A+B: Final model (M3) macro f1 extraction score on the training and development set.

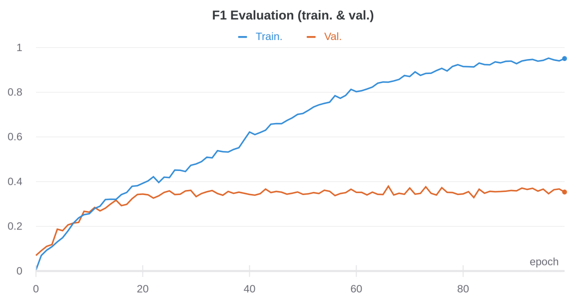

Figure 8: Task A+B: Baseline (M0) macro f1 evaluation (joint task extraction + polarity evaluation) score on the training and development set.

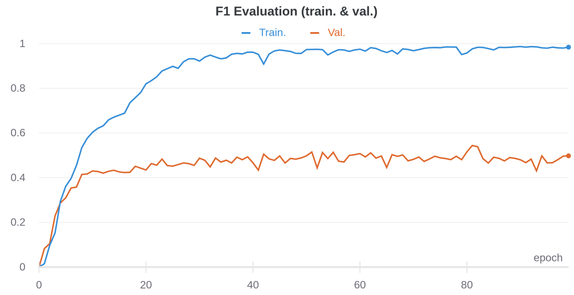

Figure 9: Task A+B: Final model (M3) macro f1 evaluation (joint task extraction + polarity evaluation) score on the training and development set.

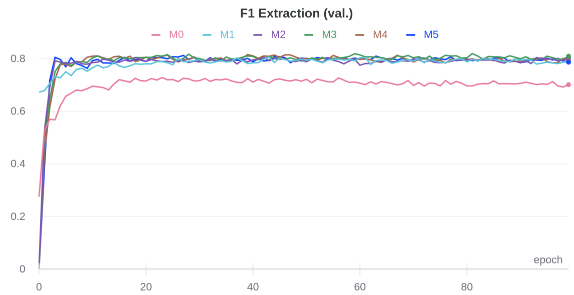

Figure 10: Task A+B: Comparative plot of f1 extraction score for the 6 model variations (M0, M1, M2, M3, M4, M5). Overall, all models (except for the baseline) seem to produce satisfying results for this task.

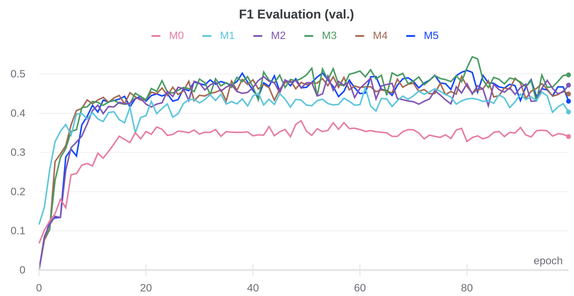

Figure 11: Task A+B: Comparative plot of f1 evaluation score (joint task extraction + polarity evaluation) for the 6 model variations (M0, M1, M2, M3, M4, M5). Even though all models works pretty much in the same way for the aspect term extraction task, the difference between the variations really starts to pop up when dealing with sentiment evaluation. This is probably due to the fact that the evaluation part requires a much more deeper understanding of the text, while the extraction part really only requires the model to exclude tokens that cannot be aspect terms (e.g., most of the times, verbs).

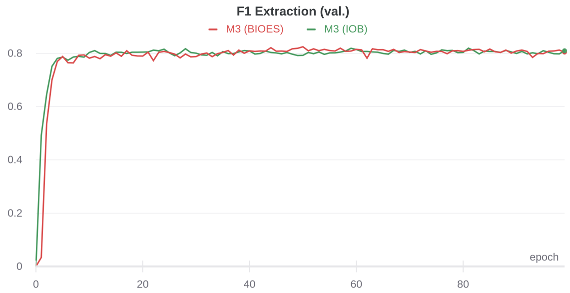

Figure 12: Task A+B: Comparative plot of f1 extraction score for the best model (M3) using two different tagging schemas (IOB, BIOES).

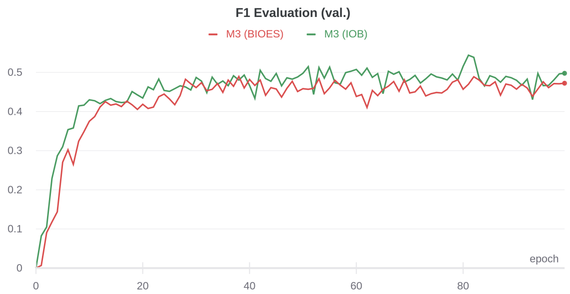

Figure 13: Task A+B: Comparative plot of f1 evaluation score for the best model (M3) using two different tagging schemas (IOB, BIOES). We can see that the proposed model just works better using the IOB schema. This could be due to the fact that, having a more difficult schema to follow, there is a higher chance of creating non-legal tag schemas (e.g., E-positive, B-positive, etc.).

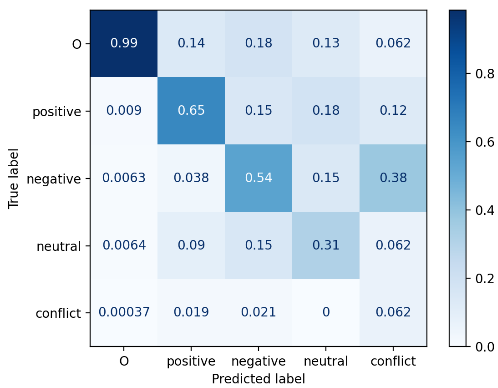

Figure 14: Task A+B: Normalized confusion matrix of the baseline model (M0).

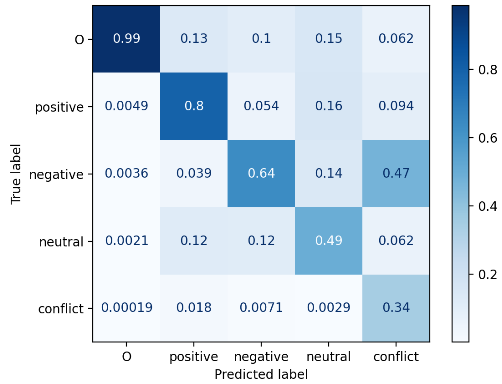

Figure 15: Task A+B: Normalized confusion matrix of the best model (M3). For both the baseline and the proposed model there is a really big gap between the performances on the positive label and the ones on the conflict label. Looking at table 1, I think one reason for this gap is given by the fact that there are much more examples in the positive class. Moreover, the conflict class is much more difficult to predict, since it must contain either some kind of uncertainty, or some mixed feelings. That could easily lead to a positive / negative classification.

Figure 16: Task C+D: Final model loss on the training and development set.

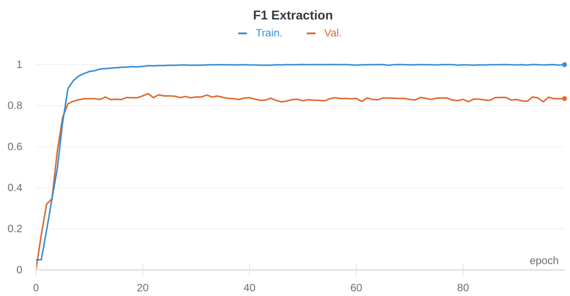

Figure 17: Task C+D: Final model macro f1 extraction score on the training and development set.

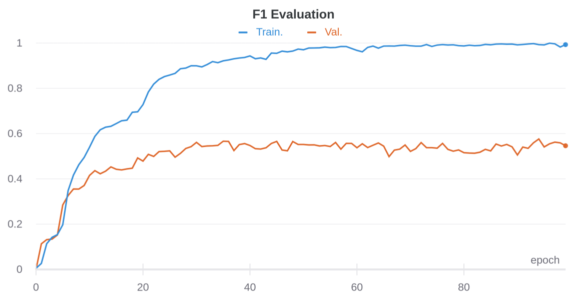

Figure 18: Task C+D: Final model macro f1 evaluation (joint task category extraction + polarity evaluation) score on the training and development set.

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