MEMBERT: Injecting Unstructured Knowledge into BERT

Abstract

Transformers changed modern NLP in many ways. However, they can hardly exploit domain knowledge, and like other blackbox models, they lack interpretability. Unfortunately, structured knowledge injection, in the long run, risks to suffer from a knowledge acquisition bottleneck. We thus propose a memory enhancement of transformer models that makes use of unstructured domain knowledge expressed in plain natural language. An experimental evaluation conducted on two challenging NLP tasks demonstrates that our approach yields better performance and model interpretability than baseline transformer-based architectures.

Keywords
Transformers · DistilBERT · Explainable AI · Memory-augmented architectures · Knowledge injection

1 Introduction

In recent years, deep learning models have produced stunning results in a wide variety of domains. In natural language processing (NLP), for instance, transformer-based architectures like BERT [1] set a new standard in many tasks, such as question answering or sentiment analysis [2]. In spite of the welcome leap in performance, however, a typical criticism transformer architectures share with most deep learning models is that they act as black-boxes, hence lacking interpretability. Sure, the attention mechanism [3] could offer cues as to how to interpret the behaviour of such models. Nevertheless, whether attention could be meaningfully used as an analysis tool is still a matter of discussion [4, 5].

In principle, deep networks could be made more interpretable by integrating domain knowledge. The idea would be to inject recognizable, readable knowledge elements into the deep network, making it inspectable. The injected information should hopefully improve the performance of the model too. This approach is gaining momentum, leading to a variety of proposals [6]. Among them, some interesting ones rely on data augmentation, model architectural biases, regularization constraints, and retrofitting. However, each architecture requires a specific knowledge representation formalism. For instance, added objective constraints are introduced by viewing background knowledge as a set of differentiable, and possibly learnable, rules [7, 8]. Unfortunately, the formalism also defines the limits of the representation, introducing the need for a costly abstraction process. For instance, in the legal domain, justifications given by experts may be valuable indicators of the underlying decision process, and as such they should be good candidates for injection. However, a structured conceptual mapping of the reasoning behind such justifications would be extremely time-consuming and hampered by referral actions, common sense motivations, and other well known issues in NLP [9]. As an example in the domain of legal analytics [10], and more specifically unfair clause detection [11], consider the following clause:

*We reserve the right to modify or terminate the service or your access to the service for any reason, without notice, at any time, and without liability to you.*

This could be considered unfair for many reasons. For instance, it gives the provider the power of *unilaterally removing consumer content* from the service, as well as *unilaterally terminating* the services. In order to link each identified unfairness category to a textual explanation interpretable by a legal expert, one could define a list of legal rationales, i.e.,...
principles that justify the legal opinion about the clause’s unfairness, and link those of them relevant to the above clause. These may be given the following textual definition:

**Unilateral Change:** *The provider has the right for unilateral change of the contract, services, goods, features for any reason at its full discretion, at any time.*

**Unilateral Termination:** *the contract or access may be terminated for any reason, without cause or leaves room for other reasons which are not specified.*

However, if knowledge injection requires to put these definitions into a formal language of some sort, a great number of additional questions arise, like which requirements have to be satisfied in order to ensure a correct usage of the knowledge provided. It is then evident that an architecture able to exploit knowledge expressed in plain English would eliminate or reduce many problems, and thus it would be extremely valuable.

In light of the above, we propose a method for injecting domain knowledge, expressed in natural language, into transformer architectures. In particular, the main contributions of the paper are the following:

1. we propose an approach to inject domain knowledge within transformer architectures, in the form of plain natural language sentences;
2. we introduce smart sampling strategies that allow to scale up to large memories, also improving the overall performance of the system;
3. we evaluate our approach on two relevant application domains, that of unfairness detection in consumer contracts, and that of claim detection in argument mining, using the DistilBERT architecture [12].

The paper is structured as follows. Section 2 discusses the integration of external knowledge and proposes a memory-augmented version of DistilBERT. We introduce memory selection supervision regularization, also known as strong supervision, and propose different attention-based sampling strategies to address scalability. Section 3 describes the experimental setting of two challenging scenarios, whereas Section 4 presents and discusses results and in-depth memory interaction analysis. Section 5 discusses similar applications of memory-based BERT architectures and the use of attention-based mechanisms to make these models’ decisions interpretable with domain knowledge. Section 6 concludes.

## 2 Problem Formulation

In this paper, we consider the problem of integrating background knowledge expressed in natural language within a transformer architecture, while achieving an interpretable model. By doing so, we distinguish ourselves from the majority of knowledge injection approaches, which assume an appropriate knowledge representation. Such setup hides the critical bottleneck of knowledge acquisition. Our case study can be informally labelled as *learning from textual descriptions*, which resembles certain human learning processes.

### 2.1 Knowledge as an External Memory

Dealing with knowledge expressed in natural language requires ad-hoc methodologies that can efficiently use it, while maintaining desired properties like model interpretability. Past research on deep learning models tackled the problem of handling external content by introducing external memory blocks with which the model could interact in a differentiable way [13]. This solution has allowed to easily handle complex reasoning tasks like reading comprehension and question answering and has also opened a new path in the context of meta-learning. On this basis, we view memory-augmented neural models as a natural architecture for natural language knowledge integration. As a major difference with such existing approaches, the knowledge we store in our memory is not core information for the task (as, for example, in question answering) but rather an auxiliary, external collection of pieces of information that can be consulted to perform reasoning and to make the neural model interpretable.

### 2.2 MemBERT: Memory-Augmented DistilBERT

The main building block of our architecture is a transformer-based model. Among the many ones, DistilBERT [12] is a distilled version of BERT that achieves competitive performance while limiting the overall computational burden. It is thus particularly convenient for running experiments. Therefore, from now on we will refer to DistilBERT specifically. However, this reference to a specific transformer-based model should not mislead the reader, since our method is applicable to any kind of neural model as a plug-and-play module. DistilBERT is enhanced with a memory layer
Figure 1: MemBERT architecture. Each textual input is encoded via the pre-trained DistilBERT layer. Subsequently, external knowledge is compared to the given input to be classified. The relevant memory content is then used to update the initial query before the final fully-connected layer for classification. We use the term $\bar{M}$, with a slight abuse of notation, to denote the employed knowledge, independently of a possible preliminary sampling strategy.

following the traditional memory-augmented neural network (MANN) architecture [14–15], whereby a neural network is extended with an external memory block supporting reasoning. We denote this model as memory-augmented BERT (memBERT). The DistilBERT layer is applied to each input, as well as to each memory slot (see Figure 1). Like in typical MANN architectures: (i) input texts are encoded via the pre-trained DistilBERT layer and memories are loaded with relevant background information; (ii) memory content is compared with the given text input via a memory-lookup layer, producing a set of similarity scores; (iii) the memory extraction layer converts similarity scores into attention scores $\{a_1, \ldots, a_M\}$ and uses them to compute a single memory summary embedding vector via a weighted sum of the memory slots; (iv) the memory summary embedding vector is eventually used to update the input embedding vector (memory reasoning). For instance, a simple form of input update consists in summing input and memory summary embedding vectors together. Lastly, a fully-connected layer is used for the classification task. In our architecture, we keep the original DistilBERT pre-classifier layer and replace the last fully-connected layer with a task-specific one. As our case studies involve independent memory slots, we do not iterate such a procedure multiple times. In the MANN jargon, this means setting the number of hops to 1. Furthermore, motivated by integrated knowledge requirements described in Section 2.1, we consider an MLP-based memory-lookup implementation. More precisely, we resort to a single dense layer with number of units in the $[32, 512]$ range. For what concerns the requirement of model interpretability, both our case studies have input examples that are associated with multiple memory slots, i.e. target memory slots. In order to obtain an interpretable model, the network has to correctly select at least one target memory slot per example. For these reasons, we adopt sigmoid-based attention scores rather than traditional softmax-based ones, being the memory slots not mutually exclusive.

The last memory-related step in the model (the reasoning layer) is implemented as a concatenation of input and memory summary embedding vectors.$^1$ Being $N$ the number of training examples and $C$ the set of classes, both DistilBERT and MemBERT are trained to minimize standard cross-entropy loss:

$$
\mathcal{L}_{CE} = -\sum_{i=1}^{N} \sum_{c=1}^{C} p(y_i = c) \log p_{\theta}(y_i = c)
$$

(1)

This setting is known in the literature as Weak Supervision (WS).

$^1$ All the mentioned architectural choices, if not explicitly motivated, have been selected after hyper-parameter tuning based on the achieved validation performance.
2.3 Guiding Memory Interaction with Strong Supervision

The concept of WS is important, since not always single memory slots can be directly associated with individual training examples. This is a very general setting. Yet, if background knowledge comes with the capability of naturally linking each example with the associated memory content, it is then possible to guide the model in the training phase by only focusing on specific target memory slots. This procedure is formally known as Strong Supervision (SS) and it has been widely explored in memory networks since their introduction [13]. SS can assume different formulations. In our experimental scenarios, it is sufficient to enforce a preference for just one of the (possibly multiple) memory slots associated with a given input example. Following [9], we limit the memory-augmented neural model to a single reasoning iteration, i.e., memory hop, and we exploit SS in the form of a max-margin loss. More precisely, we do not perform target sampling to ensure both the presence of negative and positive examples, but we instead rely on batch examples to formulate the constraint.

Formally, we define target memory slots as those that have been linked to the input example during the annotation phase. We introduce a loss penalty term that enforces target memory slots to have a higher similarity score with respect to the input than to the remaining slots, up to a γ margin:

\[
L_{SS} = \frac{1}{N} \sum_{n=1}^{N} \frac{1}{|M^+_n||M^-_n|} \sum_{m_+ \in M^+_n} \sum_{m_- \in M^-_n} [L(m_+, m_-)]
\]

\[
L(m_+, m_-) = \max \left(0, \gamma - \sigma(s(q^n, m_+)) + \sigma(s(q^n, m_-))\right)
\]

where \(M^+_n\) is the set of target memory slots for a given input example \(q^n\), \(M^-_n\) is the set of non-target memory slots for the \(n\)-th input example, \((m_+, m_-)\) is a target/non-target memory slot pair for \(n\), and \(\sigma\) is the (sigmoid) activation function. The hyper-parameter \(\gamma\) controls the intensity of the SS constraints, while trading-off classification performance and model interpretability: large values of \(\gamma\) would basically turn the preference ranking induced by the hinge loss into a classification loss. Overall, the loss function for MemBERT with SS is:

\[
L = L_{CE} + L_{SS}
\]

2.4 Efficiently Handling Large Memories with Sampling

Dealing with complex deep learning models and large knowledge bases requires an efficient retrieval of relevant content while maintaining scalable memory usage. To this end, approximate solutions or sampling-based methods have been explored, trading-off performance with efficiency [16]. However, such solutions are mainly focused on simple comparison strategies like dot product similarity that are easily executed in parallel and approximated. In our case, we aim to define a more complex memory lookup phase. Therefore, we allow neural-based similarities and strive to look for an efficient sampling strategy to achieve scalability.

Memory sampling brings about both benefits and, possibly, issues. Reducing the overall memory size enables large knowledge integration when dealing with complex deep neural models like DistilBERT. Moreover, sampling eases the knowledge integration process from the point of view of noise compensation. In a similar fashion to curriculum learning [17], sampling reduces complexity by considering a smaller memory, which, in turn, induces a limitation of spurious lookup operations. This is also reflected at training time, where in each batch the model sees a different memory, thus avoiding to always focus on specific slots, which could possibly lead to overfitting. Nonetheless, sampling inherently introduces variance, therefore compatibility issues with other strategies like strong supervision might arise as well. To compensate for both problems, it is crucial to define smart sampling strategies that can be conditioned on input examples. To this end, similarly to prioritized experience replay (PER) [18], employed in reinforcement learning, we introduce priority-based sampling strategies that progressively take into account the importance of the added information with respect to both input examples and task objectives. In particular, to efficiently deal with large memories, we operate at batch level by sampling a shared knowledge base. Then, depending on the given strategy, priority weights \(p_{m_i}\) associated to each memory slot \(m_i\) are updated and available for the next batch step. More precisely, we adopt the same priority definition of PER, where the temporal difference (TD) error is replaced by a custom importance assignment function:

\[
p_{m_i} = (w_{m_i} + \epsilon) ^\alpha
\]

where \(w_{m_i}\) is the importance weight of the \(i\)-th memory slot \(m_i\), \(\epsilon\) is a sufficiently small real value that avoids zero-based exponentiation and \(\alpha\) controls the priority degree. Intuitively, \(\alpha\) equal to 0 produces all priorities equal to 1, thus defining a uniform sampling strategy. Lastly, sampling is applied both at training and at inference time, when learnt priority weights are employed to sample the memory. Algorithm 1 formally describes the training sampling procedure, while Algorithm 2 describes the inference sampling procedure. Introduced strategy variants differ on how priority weights are updated at each batch step.
Algorithm 1: General Training Sampling Procedure

**Input:** Data $D = \{ (x_n, y_n) \}_{n=1}^N$, Memory priority weights distribution $p|M|$, Model weights $\theta$

1. Initialize model weights $\theta = \theta^0$
2. Initialize memory priority weights $p|M| = p^0|M|
3. repeat
   4. Sample a minibatch $k$, $B^k = (X, Y) \subset D$
   5. Sample memory $\bar{M}$ using $p_{k-1}|M|$
   6. Compute model loss $L(x|\bar{M})$ on minibatch $B$
   7. Update model parameters $\theta^k$ using any optimizer
   8. Compute memory importance weights $w^k|M|$
   9. Update memory priority weights $p^k|M| = (w_{mi} + \epsilon)\alpha$
   10. Normalize $p^k|M|$ to get corresponding distribution
4. until stopping criteria
5. Save memory priority weights $p|M|

**Output:** Trained model weights $\theta$, trained sampler priority weights $p|M|$

Algorithm 2: General Inference Sampling Procedure

**Input:** Data $D = \{ (x_n, y_n) \}_{n=1}^N$, Learnt memory priority weights distribution $p|M|

1. repeat
   2. Get next inference minibatch $k$, $B^k = (X) \subset D$
   3. Sample memory $\bar{M}$ using $p|M|$
   4. Save model predictions $\hat{Y}$
5. until $B^k \in \emptyset$

**Output:** Model predictions and sampled memory $\{ (\hat{y}_n, \bar{M}_n) \}_{n=1}^N$

2.4.1 Uniform Sampling

As a baseline strategy we consider uniform memory sampling. At each batch, each memory slot has the same probability of being selected. Priorities are kept fixed during training. Formally, being $|M|$ the memory size, we define the probability of sampling each memory slot $m_i$ as $p_{m_i} = \frac{1}{|M|}$.

2.4.2 Priority Sampling

Intuitively, uniformly sampling from memory immediately relieves us from the problem of handling a large knowledge base, but it does not take into account the importance of each slot. For instance, we would like to retrieve memory slots depending on the characteristics of each input batch. In order to do that, at training time, each individual input example should be able to modify the underlying sampling distribution by giving more priority to those memory slots that have been reputed useful. Thus, we introduce priority sampling following the same perspective of PER [18]. In particular, we explore two different formulations of priority that ground the notion of usefulness to a specific architectural property of the model. More precisely, we consider the memory attention layer as the major indicator of importance of each memory slot with respect to the given input example, considering two variants: (i) the first one relies exclusively on the attention value of each memory slot, whereas (ii) the second formulation also takes into account the contribution of each memory slot to the overall objective of training (i.e., the classification loss).

Attention-Based Priority Sampling In this formulation, the priority associated to each memory slot during sampling is based on the corresponding attention value computed by the memory lookup layer. In particular, working with batches inherently requires a consistent reduction operation that summarizes each memory slot importance at batch level. To this end, we consider a masked average based reduction, which considers the mean attention value of each memory slot for a certain class of input examples. This strategy accounts for noise introduced by input examples that are not interested by the background knowledge. For instance, in the case of a binary classification task where memory
contains valuable information for the positive class only, we should limit sampling priority update to positive examples, to avoid spurious memory selections.

Formally, the attention-based priority sampling defines each memory slot importance as its summary attention value in the batch.

\[ w_{m_i} = \frac{\sum_{j} |B| a_{j,i}}{\sum_{j} |B| \mathbb{1}_{y_j \in Y^+}} \]  

where \( a_i \) is the attention value attributed to memory slot \( i \), \( |B| \) is the batch size and \( Y^+ \) is the set of examples belonging to the positive class.

Note that this strategy is purely similarity-based and it does not take into account the contribution of each memory slot to the task-specific objective. In other terms, it operates under the assumption that each knowledge descriptive concept contained in the memory should have high semantic and syntactic similarity with its associated input examples. Thus, it might not be suitable in cases where input examples have high similarity with unrelated memory slots due to their natural language formulation.

**Loss Gain Priority Sampling** In order to render priority sampling aware of the usefulness of each memory slot to the task itself, we consider an additional variant that directly exploits the classification loss. In particular, we consider the loss difference between the standard model architecture and the one augmented with the memory layer. By doing so, we are able to estimate the informative gain introduced by the external knowledge with respect to the task. The larger is the difference, the larger is the impact of the memory. To associate a specific priority value to each memory slot \( m_i \), we consider the same reduction operation strategy adopted for attention-based priority sampling. Formally, this loss gain priority sampling can be formulated as follows:

\[ w_{m_i} = \frac{\sum_{j} |B| a_{j,i} \exp(L_{CE}(x_j) - L_{CE}(x_j | \bar{M}))}{\sum_{j} |B| \mathbb{1}_{y_j \in Y^+}} \]  

where \( a_i \) is the attention value attributed to memory slot \( i \), \( \bar{M} \) is the sampled memory, \( L_{CE}(x) \) and \( L_{CE}(x | \bar{M}) \) are the cross-entropy loss obtained without any interaction with the memory, or with the introduction of the sampled memory \( \bar{M} \), respectively. The exponential guarantees a positive priority while awarding positive differences with high values and down-weighting negative differences.

### 3 Experimental Setup

To test our approach, we consider two distinct classification scenarios. In the first, we extend the work in [9] focusing on the legal domain for unfair clause detection in online Terms of Service, by employing explanations given by legal experts as domain knowledge. In the second scenario, we explore the argument mining case study of claim detection by employing evidence information as knowledge source, following the assumption that class correlation might ease the classification task. To ensure reproducibility, we made all our code and data available at the following repository: [https://bitbucket.org/hl2exe/membert/](https://bitbucket.org/hl2exe/membert/).

#### 3.1 Knowledge as Class Descriptions: Unfairness Detection

Following [9], we formulate the problem of unfair clause detection in online Terms of Service as a binary classification task, enriched by legal expertise in the form of rationales, that is explanations of unfairness. It is a well-known fact that online Terms of Service too often contain clauses that are potentially unfair for the consumer, and NLP tools have been proven successful in detecting them [11]. In our setting, each clause is the input text to be classified, and the set of legal rationales defines the shared memory.

##### 3.1.1 Data

The corpus originally published in [9] defines legal rationales for five unfairness categories following a multi-label perspective (i.e., a clause can be unfair according to more than a single category). These categories are: arbitration on disputed arising from the contract (A); the provider’s right to unilaterally modify the contract and/or the service (CH); the provider’s right to unilaterally remove consumer content from the service, including in-app purchases (CR); liability exclusions and limitations (LTD); the provider’s right to unilaterally terminate the contract (TER). We randomly extracted 30 documents while ensuring that they contained at least one example per unfairness category. Table 1 reports some statistics on the corpus, which we name ToS-30, showing the number and percentage of unfair clauses per
Table 1: Corpus statistics for ToS-30. For each category of clause unfairness, we report the number and percentage of unfair clauses, and the number of rationales.

| Type of clause         | # unfair clauses | % unfair clauses | # rationales |
|------------------------|------------------|------------------|--------------|
| Arbitration (A)        | 45               | 0.8              | 8            |
| Unilateral change (CH) | 89               | 1.7              | 7            |
| Content removal (CR)   | 58               | 1.1              | 17           |
| Limitation of liability (LTD) | 161 | 3.0 | 18 |
| Unilateral termination (TER) | 121 | 2.3 | 28 |

category, as well as the amount of corresponding legal rationales defined by experts. More technical details concerning the definition of both the unfairness categories and the rationales can be found in [9].

3.1.2 Setting

As in [9], we consider each unfairness category individually. In particular, for a given unfairness category, we consider as positive examples those who have been labeled as being unfair for the given category, while the remaining sentences are viewed as not unfair. As competitors for our approach, we consider the following neural baselines: (i) 2-layer CNN network; (ii) 1-layer bi-LSTM network; (iii) MANN baseline as in [9]. Neural baselines use 512-dimensional embeddings, whereas the MANN baseline uses 256-dimensional embeddings. All the embeddings are learnt from scratch. Additionally, models are further regularized with $L_2$ penalty with $10^{-5}$ weight, dropout rate in the $[0.5, 0.7]$ range and are optimized with Adam optimizer with $10^{-3}$ learning rate. For evaluation, we employ a 10-fold cross-validation procedure. As a regularization criterion, all models are early stopped based on the validation F1-score, with a patience equal to 10 for BERT models and to 50 for other neural baselines.

3.2 Knowledge as Supporting Facts: Claim Detection

The second scenario of interest is claim detection in the context of argument mining [19]. In particular, we formulate the problem as a binary classification task where each input sentence can be either identified as containing a claim or not. Here, background knowledge is expressed by the set of labelled evidence that can potentially support a claim. Thus, we aim to investigate whether evidence, which usually back up claims, bring some benefit to the task of claim detection.

3.2.1 Data

We consider a portion of the IBM2015 argumentative corpus, built in the context of the Debater project [20, 21]. The dataset consists of a collection of Wikipedia pages, grouped into topics. The annotation procedure carried out by IBM is context-dependent, which means that claims and evidence are annotated with the assumption that the topic (context) is given. In our scenario, we selected the four topics with the largest amount of claims and evidence. Subsequently, we defined the set of evidence as the model memory. Due to how argumentative texts were annotated, there are cases in which a single sentence may contain both a claim and evidence or, more seldom, an evidence spans through multiple sentences and incorporates a claim. Indeed, these cases hinder the quality of selected data, but due to the low amount of such spurious sentences, we do not consider further pre-processing steps and use the corpus as is. Table 2 reports details about the selected subsets of topics, focusing on their argumentative content. We remark that evidence in the IBM2015 dataset are typically statements extracted from studies or facts established by experts: it is thus a reasonable assumption to have a list of such items available to support claim detection.

3.2.2 Setting

As for unfairness detection, we consider sentence-level binary classification task for claim detection. More precisely, each sentence can either be identified as containing a claim or not. To progressively evaluate the benefits of added knowledge, we consider incremental subsets of topics, from 1 up to 4. However, differently from the legal domain case study, the memory content drastically increases as the number of topics gets larger, from 130 with a single topic up to 642 with four topics. Additionally, the number of claims associated to each evidence is very low (range 1-5). Thus, a

Note that the corpus labeling procedure distinguishes between potentially unfair and clearly unfair clauses, but following [9] we merged these categories together.

We initially trained for 3-4 epochs as a well known good practice, but we immediately saw that more epochs were required to achieve significant performance.
Table 2: Topics extracted from the IBM2015 corpus, with associated number of evidence and claims. For claims, we also report the percentage with respect to the overall corpus size, which corresponds to the frequency of the positive class.

| Topics | No. Evidence | No. Claim | Claim Ratio |
|--------|--------------|-----------|-------------|
| 1      | 130          | 113       | 4.2%        |
| 2      | 239          | 201       | 4.0%        |
| 3      | 578          | 288       | 3.8%        |
| 4      | 642          | 374       | 3.5%        |

correct usage of memory and of strong supervision is extremely challenging. Moreover, such issue completely hinders the full knowledge scenario with MemBERT, i.e., the one where the model sees the whole memory content, due to memory issues. Inevitably, in this scenario there is need to enforce the adoption of a sampling strategy.

Given the low amount of samples, models are evaluated via a $k$-fold cross-validation procedure (we chose $k=4$). As for unfairness detection, we employed the multi-start technique with 3 repetitions, choosing the best one according to the validation F1-score. At training time, models follow the same regularization setup employed for unfair clause detection, by applying early stopping on the validation F1-score. Patience is set to 10 for BERT models and 50 for other neural baselines. The MANN baseline uses 50-dimensional embeddings, whereas all the other hyper-parameters are identical to the ToS-30 setting.

### 3.3 Memory Analysis

Knowledge integration evaluation cannot be reduced to task-specific metrics only. Albeit by adding more knowledge one would expect increased classification performance, there are other dimensions on which such integration could bring benefit. For instance, natural language is inherently straightforward to interpret. Thus, correctly linking such content to the input would enrich the model with properties that compensate slight fluctuations with respect to the achieved classification performance. Under this critical perspective, we evaluate MemBERT to assess whether knowledge integration is effective and to what extent.

As an initial step, we consider several memory-related metrics already introduced in [9]. These metrics evaluate knowledge integration under several perspectives, covering typical information retrieval analysis concerning top-K memory ranking, as well as purely memory-oriented statistics like target coverage. Such metrics will also be employed to analyze the behavior of sampling in domains where memory size is intractable. For space issues, we only select a limited amount of these metrics by picking the most informative ones:

- **Memory Usage (U)**: percentage of examples for which memory is used.
- **Coverage (C)**: percentage of positive examples for which (at least one) memory slot selection is correct.
- **Coverage Precision (CP)**: percentage of examples using memory, for which (at least one) memory slot selection is correct.
- **Precision at K (P@K)**: percentage of positive examples for which at least one correct memory target is retrieved in the first K positions.
- **Mean Reciprocal Rank (MRR)**: average of the reciprocal memory ranks.

A natural issue that arises when dealing with soft memory interactions is to define an appropriate activation threshold $\delta$, i.e., the minimum value to consider a memory slot has been used by the model. Indeed, even though with SS regularization we explicitly enforce a specific activation threshold $\gamma$, in the experimental setup the desired setting might not be feasible at all. For instance, in the IBM2015 corpus, there are several factors that might hinder such type of regularizations. More precisely, the large scale knowledge base and the presence of evidence that are semantically close to non target claims, prevents accentuated memory selections. To this end, in that setting we explore memory-related metrics with variable activation thresholds, so as to measure to what extent the model is capable to focus on certain memory slots.

### 4 Results

We hereby describe the results obtained on the two scenarios, both considering standard classification metrics, and providing an analysis of the memory usage.
Table 3: Classification macro-F1 computed on 10-fold cross-validation for unfair examples on the ToS-30 dataset. WS and SS stay for weak and strong supervision, respectively. Sampling employs a 5-slot reduced size memory. We compare uniform (U), priority attention only (P-Att) and priority loss gain (P-LG) strategies. Priority sampling always considers negative example filtering (F) for correct priority update. Best results are in bold, second best results are underlined.

|                | A  | CH | CR | LTD | TER |
|----------------|----|----|----|-----|-----|
| **No Knowledge** |    |    |    |     |     |
| CNN            | 0.339 | 0.506 | 0.403 | 0.628 | 0.583 |
| LSTM           | 0.302 | 0.573 | 0.363 | 0.602 | 0.508 |
| DistilBERT     | 0.447 | **0.635** | 0.620 | 0.670 | **0.748** |
| **Full Knowledge** |    |    |    |     |     |
| MANN (WS)      | 0.483 | 0.506 | 0.387 | 0.635 | 0.602 |
| MANN (SS)      | 0.465 | 0.516 | 0.414 | 0.605 | 0.660 |
| MemBERT (WS)   | 0.494 | 0.565 | 0.639 | 0.664 | 0.705 |
| MemBERT (SS)   | **0.504** | 0.609 | **0.670** | **0.686** | 0.737 |
| **Sampling**   |    |    |    |     |     |
| MemBERT (WS) (U-5) | **0.514** | 0.556 | 0.609 | 0.678 | 0.702 |
| MemBERT (WS) (P-5-Att-F) | 0.491 | 0.559 | 0.601 | 0.643 | 0.703 |
| MemBERT (WS) (P-5-LG-F) | 0.475 | 0.574 | **0.660** | 0.678 | 0.716 |
| MemBERT (SS) (U-5) | 0.503 | 0.580 | 0.617 | 0.652 | 0.702 |
| MemBERT (SS) (P-5-Att-F) | 0.448 | 0.599 | 0.635 | 0.661 | 0.708 |
| MemBERT (SS) (P-5-LG-F) | 0.490 | 0.536 | 0.625 | 0.656 | 0.706 |

4.1 Unfairness Detection

For what concerns unfair clause detection, Table 3 summarizes the results obtained on the ToS-30 corpus, by reporting the macro-F1 averaged on 10-fold cross-validation. A first, clear result is that all BERT models maintain a large performance gap over the other neural baselines. The introduced legal rationales significantly aid memory-augmented models in categories for which there are few positive examples like A and CR. On the other hand, on category CH we can observe that memory-based approaches do not show an improvement over their counterparts: MANNs perform worse than LSTMs, and MemBERT performs worse than DistilBERT. This behavior might hide a problem in the nature of the natural language rationales given for the CH category, which are evidently less informative than those given for the other categories. The introduction of SS regularization always leads to better performance for MemBERT models that leverage full knowledge. In particular, it is particularly beneficial for categories with increased memory size like CR, LTD and TER. Sampling-based models manage to reach performance comparable with their full knowledge counterparts. However, memory sampling attenuates the added contribution of SS regularization, leading to mixed results for different strategies.

Regarding the usage of memory, Table 3 reports statistics concerning the predictions of our models on unfair examples. The results clearly show that SS brings a crucial contribution in giving high importance to the correct memory slots: in all the categories, one correct memory slot is ranked in the top 3 positions in over 55-80% of the cases. This behaviour is reflected also in the MRR score which shows a clear advantage of SS over WS.

4.2 Claim Detection

As for the claim detection scenario, Table 5 reports the achieved experimental results on the four considered subsets of topics. As for unfair clause detection, we evaluate knowledge-agnostic neural baselines as well as MANN models. First of all, we note how MANNs achieved significant improvements over CNNs and LSTMs, suggesting that the introduced knowledge is indeed beneficial to the task itself. Similarly, MemBERT achieves higher F1-score with respect to standard DistilBERT. Interestingly, even the uniform sampling strategy manages to outperform other neural baselines, meaning that sampling also acts as a noise compensation operator, thus, easing the process of knowledge integration while increasing model robustness. This behaviour is accentuated for MANNs, where the combination

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4Legal rationales for CH category are very similar to each others, with minor distinctions that might be hard to discriminate without supervised guidance.
Table 4: Memory statistics concerning predictions on unfair examples only. Memory interaction is evaluated on ToS-30 test set. We report memory usage (U), the correct memory usage over unfair examples (C) and over examples for which memory is used (CP), along with a more fine-grained ranking version (P@1-3) and the mean reciprocal rank (MRR). Due to different memory usage, columns C–P@3 are not directly comparable. We set activation threshold $\delta$ to 0.5.

| Model       | U     | C     | CP    | P@1  | P@3  | MRR  |
|-------------|-------|-------|-------|------|------|------|
| Arbitration (A) |       |       |       |      |      |      |
| MANN (WS)   | 0.311 | 0.289 | 0.929 | 0.571| 1.000| 0.761|
| MANN (SS)   | 0.689 | 0.644 | 0.935 | 0.903| 0.968| 0.861|
| MemBERT (WS)| 0.489 | 0.400 | 0.818 | 0.273| 0.545| 0.478|
| MemBERT (SS)| 0.956 | 0.911 | 0.953 | 0.767| 0.837| 0.848|
| Arbitration (CH) |       |       |       |      |      |      |
| MANN (WS)   | 0.169 | 0.090 | 0.533 | 0.000| 0.067| 0.299|
| MANN (SS)   | 0.854 | 0.730 | 0.855 | 0.855| 0.961| 0.883|
| MemBERT (WS)| 0.404 | 0.382 | 0.944 | 0.250| 0.750| 0.522|
| MemBERT (SS)| 1.000 | 0.955 | 0.955 | 0.809| 0.888| 0.886|
| Arbitration (CR) |       |       |       |      |      |      |
| MANN (WS)   | 0.017 | 0.000 | 0.000 | 0.000| 0.000| 0.335|
| MANN (SS)   | 0.672 | 0.414 | 0.615 | 0.282| 0.872| 0.612|
| MemBERT (WS)| 0.328 | 0.328 | 1.000 | 0.316| 0.632| 0.478|
| MemBERT (SS)| 1.000 | 0.948 | 0.948 | 0.431| 0.879| 0.681|
| Arbitration (LTD) |       |       |       |      |      |      |
| MANN (WS)   | 0.037 | 0.025 | 0.667 | 0.33 | 0.833| 0.504|
| MANN (SS)   | 0.814 | 0.534 | 0.656 | 0.313| 0.573| 0.501|
| MemBERT (WS)| 0.497 | 0.416 | 0.838 | 0.100| 0.275| 0.328|
| MemBERT (SS)| 1.000 | 0.919 | 0.919 | 0.224| 0.565| 0.474|
| Arbitration (TER) |       |       |       |      |      |      |
| MANN (WS)   | 0.000 | 0.000 | 0.000 | 0.000| 0.000| 0.499|
| MANN (SS)   | 1.000 | 0.471 | 0.471 | 0.438| 0.537| 0.536|
| MemBERT (WS)| 0.223 | 0.198 | 0.889 | 0.074| 0.074| 0.193|
| MemBERT (SS)| 1.000 | 0.851 | 0.851 | 0.438| 0.579| 0.567|

of SS and priority sampling largely outperforms the version with full knowledge. More precisely, for 1 and 2 topics MANNs nearly match DistilBERT, yet with a drastically lower number of parameters. These results corroborate the hypothesis that controlled and smart knowledge integration can be particularly beneficial when limited training data is available. Differently from unfairness detection, the large memory size hinders selective memory lookup operations. Thus, metrics are computed over incremental values of activation threshold $\delta$. In particular, we mainly focus on the P@K metric, since it is a valuable indicator of the model retrieval capabilities. Figures 2a reports values of P@K on the 1-Topic case, along incremental value of $K$, with fixed $\delta = 0.25$, whereas Figure 2b reports P@3 with incremental $\delta$ values. In both cases, we can clearly see how loss gain priority sampling coupled with SS (P-10-LG-F) is the setting that achieves the best performance.

5 Related Work

A recent trend regarding combining memory-augmented architectures with transformer architectures views the memory component as an auxiliary support for efficient learning. More precisely, specific effort is dedicated to solving the well-known problems of handling long-term dependencies, as well as of processing long sequences. One common idea is to reduce the search space by progressively storing intermediate input representations in the memory component. Notable examples are Transformer-XL [22], Reformer [23], LongFormer [24] and MemFormer [25]. More precisely, in these architectures the memory component is directly inserted as an intermediate layer in the transformer architecture, mainly addressing the multi-head attention step in order to condition token selection.
MemBERT: Injecting Unstructured Knowledge into BERT

Figure 2: Memory analysis on IBM2015, 1-Topic. Left: P@K for increasing \( K \) values and \( \delta = 0.25 \). Right: P@3 for increasing \( \delta \) values. Metrics for sampling-based models are averaged across three distinct inferences on the test set.

Table 5: Classification performance for dataset IBM2015. For each topics subset, we report the achieved macro F1-score. WS and SS stay for weak and strong supervision, respectively. Memory sampling is tested with a 10-slot reduced size memory. We report the uniform strategy (U), the priority attention only strategy (P-Att) and the priority loss gain strategy (P-LG). Priority sampling always considers negative example filtering (F) for correct priority update. Best results are in bold, second best results are underlined instead.

|                | 1 Topic | 2 Topics | 3 Topics | 4 Topics |
|----------------|---------|----------|----------|----------|
| **No Knowledge** |         |          |          |          |
| CNN            | 0.196   | 0.283    | 0.287    | 0.268    |
| LSTM           | 0.194   | 0.344    | 0.278    | 0.272    |
| DistilBERT     | 0.317   | 0.431    | 0.405    | 0.451    |
| **Full Knowledge** |         |          |          |          |
| MANN (WS)      | 0.252   | 0.380    | 0.325    | 0.336    |
| MANN (SS)      | 0.205   | 0.392    | 0.317    | 0.281    |
| **Sampling**   |         |          |          |          |
| MANN (WS) (U-10) | 0.269   | 0.406    | 0.331    | 0.355    |
| MANN (WS) (P-10-Att-F) | 0.251   | 0.402    | 0.322    | 0.358    |
| MANN (WS) (P-10-LG-F) | 0.259   | 0.408    | 0.332    | 0.340    |
| MANN (SS) (U-10) | 0.297   | 0.400    | 0.319    | 0.352    |
| MANN (SS) (P-10-Att-F) | 0.264   | 0.423    | 0.332    | 0.348    |
| MANN (SS) (P-10-LG-F) | 0.302   | 0.424    | 0.344    | 0.354    |
| MemBERT (WS) (U-10) | 0.311   | 0.457    | **0.454**| **0.453**|
| MemBERT (WS) (P-10-Att-F) | 0.275   | 0.449    | 0.422    | 0.434    |
| MemBERT (WS) (P-10-LG-F) | 0.305   | 0.449    | 0.428    | 0.428    |
| MemBERT (SS) (U-10) | 0.341   | 0.442    | **0.444**| 0.436    |
| MemBERT (SS) (P-10-Att-F) | **0.354**| 0.424    | 0.421    | 0.423    |
| MemBERT (SS) (P-10-LG-F) | 0.290   | **0.459**| 0.411    | 0.444    |

In a similar fashion, but with different intent, transformers have been augmented with an external memory block in order to efficiently deal with data. This means handling complex input sequences like videos [26] by overcoming the natural sequential information flow and learning global-level corpus information. In the latter scenario, global and local attention mechanisms have been combined by means of learnable parameter vectors [27][28] that account for word meanings in different context throughout the corpus [29].

Another well-known use of the memory block is for external knowledge integration. In this scenario, contributions are mainly distinguished by the type of available knowledge and by the task of interest. Transformers have been directly applied as advanced input encoding methods in traditional memory-augmented architectures for information retrieval,
dialogue systems [30, 31] and question-answering [32]. Similarly, this combined model has been used to tackle other well-known tasks like aspect-based sentiment analysis [33]. In particular, in all these scenarios, the memory block is employed to store textual passages that are specific of each individual dataset example, either given as an additional input like question-answering [34] or attentively extracted from a set of documents following an information-retrieval phase [30]. Under the same perspective, knowledge bases have also been encoded as external memory. Differently from our setup, in this scenario each memory slot encodes a single word or entity tuples [35, 36] and the underlying intent is to expand the contextual information of words to ease the learning process. More precisely, knowledge as a richer complementary vocabulary is just one of its possible formulations. Indeed, with knowledge in the form of sentences in natural language we cover several scenarios of different nature, spanning from additional contextual information to general task-oriented constraints. For instance, the memory could contain textual descriptions of the task itself and, thus, we could formulate the task of learning from them while ignoring labels, thus resembling human learning.

Clearly, when dealing with transformer architectures, one major challenge is interpretability. Many attempts at building interpretable NLP models are based on the attention mechanism [3]. Although attention can be used to interpret the behaviour of deep neural networks [37], whether it can also be considered a proper explanation tool is still an open debate, which hinges on the definition of explanation itself. In fact, while attention provides a possible interpretation of a network’s behaviour, it is not possible to guarantee whether that interpretation is the right one [4, 5]. Therefore, we can consider attention weights to be an explanation if we define them as a plausible, but not necessarily faithful, reconstruction of the decision-making process [38, 39]. It can be argued that attention is not consistent with other explanation methods [3], but the same characteristic has been observed in many other popular explanation tools [40]. Attention has also been used as a means to integrate knowledge in models by specifically training it to select relevant features [41, 42] or to model an auxiliary task [43, 44]. On a slightly different perspective, the “interpretability illusion” of BERT-related models has been described as the phenomenon for which individual neurons in BERT not always show a human-interpretable meaning [45]. More in general, the use of background knowledge to make deep learning systems more explainable and interpretable has been explored with knowledge graphs [46], whereas another recent approach proposes to store commonsense knowledge in an external symbolic memory that interacts with the neural model [47].

6 Conclusions

In this paper, we introduced the general problem of unstructured knowledge integration within BERT models. In particular, we proposed a memory-augmented version of DistilBERT that follows the traditional MANN architecture. We explored two challenging experimental settings: (i) class descriptions for unfair clause detection in the legal domain and (ii) evidence as support for claim detection in the context of argumentation mining.

In spite of a rather straightforward formulation, promising results have been achieved concerning classification performance and interpretability. Most notably, when strong supervision is applied, memory-augmented models learn to correctly select target memory slots with high precision and, in most cases, reach higher performance. Memory sampling allows to scale up to large knowledge bases. In particular, priority-based sampling strategies reach more consistent performance from the viewpoint of both classification and interpretability.

The underlying potential of unstructured knowledge integration is particularly vast, since expert information in plain natural language is easy to acquire. Many other domains could thus benefit from the proposed kind of approach.

In the future, we plan to explore several research directions. We will apply this methodology to text generation, for example for argument generation. Furthermore, we have always considered a fixed memory content, whereas, certainly, knowledge integration might benefit from a dynamic formulation [8]. Correctly handling examples not covered by the integrated knowledge still stands as an open problem. Lastly, more sophisticated memory interaction mechanisms will be investigated to improve the performance of the approach.

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