In this work we study the presence of expert units in pre-trained Transformer Models (TMs), and how they impact a model’s performance. We define expert units to be neurons that are able to classify a specific concept with a given average precision, hence being able to correctly classify a future ball’s passing or shooting angle. We find that many multi-category TMs are specifically trained to indicate the accuracy of a given concept when following the instructions of a pre-specified skill coach and/or observers. In this experiment we test this hypothesis, using TMs that specialize in the shooting skills of throwing and catching.

Figure 1: Example of generated text by GPT2-L conditioned on the WordNet concept football%1:04:00 by forcing only its top 50 expert units (0.012% of the 414720 units analyzed) as determined by our interpretation method detailed in Section 4.1. The beginning of this paper’s abstract is given as context (gray). Neither the interpretation nor the conditioning require re-training, fine-tuning or using additional parameters. Note the strong presence of concept football%1:04:00 in the generated text, including words like ‘coach’ or ‘shooting’. Even more interesting is how the term ‘TM’ appears in a sporting sense, and how TMs ‘specialize’, taking the initial context also into account.
expert units. We hypothesize that the presence of expert units is related to the knowledge acquired by TMs and to their performance.

Previous work in image processing has shown that CNNs and GANs learn representations of specific objects at a filter level [3, 4] and by filter combinations [11], even if those objects were never explicitly labeled during training. The key idea behind these works is to consider CNN feature maps as segmentation masks, which allows quantifying the coherence with a densely labeled image by means of intersection over union (IOU). These works have also inspired our research, however there are fundamental differences in our work: (1) In NLP it is harder to define a concept with a single sentence, thus we propose to represent concepts with sets of positive and negative sentences as explained in Sec. 3. We collect a total of 1641 concepts, leveraging the OneSec dataset [32]. (2) We consider the most basic units in TMs, the neurons, as expert unit candidates, which allows computing average precision AP (i.e., area under the precision-recall curve) to quantify how a unit is able to disambiguate a concept. (3) Since sentences can be of arbitrary length, we maxpool the unit responses in time to be invariant to length. The proposed method to identify and rank experts is detailed in Sec. 4.1.

In Sec. 4.2 we define a metric called concept expertise, and we show that it is strongly correlated ($r^2 = 0.833$) with the generalization power of TMs. As a measure for model generalization we use the average performance on diverse downstream tasks: all GLUE tasks + SQuAD v1.1/2.0. We propose an empirical method to compute the optimal expertise level that maximizes the correlation between generalization and expertise. The obtained expertise (AP above 0.985) shows that generalization is related to the presence of extremely good and diverse experts. Our definition of expertise enables the ranking of TMs without fine-tuning on large suites of downstream tasks (current practice), mitigating the need for hyper-parameter search and the problem of downstream task bias [24]. Moreover, the proposed concept dataset can be easily enriched for finer model comparison.

In Sec. 5 we show that concepts with similar meaning are co-learnt by a certain number of experts. We define concept overlap to quantify co-learning, and we show its utility for concept explainability.

The presence of experts is also exploited in Sec. 6 to self-condition a pre-trained language model (LM) to generate text that contains a specific concept (see Fig. 7 for an example). We base our approach on the product of experts formulation introduced by [14] and adapted to image generative models by [23] by training an external conditional expert. In addition to applying the product of experts formulation to a new domain (NLP) and new architecture (TM), a notable difference is that we consider that conditional experts already exist in the pre-trained model. The results in Sec. 6.1 show that only a small number of experts is required to induce a concept in the model output, supporting our hypothesis. Other works have tackled LM conditioning [17, 30, 6, 18], all based on learning disentangled concepts during training. To the best of our knowledge, our work is the first to condition an off-the-shelf pre-trained LM without fine-tuning, re-training or using additional parameters. Furthermore, our method is extremely simple to implement.

2. Related work

The NLP community is experiencing a sharp increase in interpretation methods. We focus on those exploring Transformer architectures, which are the keystones for most of the recent top-performing models.

Saliency Some works focus on analyzing the self-attention layers in the Transformer blocks, visualizing saliency [12] or studying how attention heads attend to different word families [17]. The analysis of attention layers usually results in a word-word relationship, which can make it hard to extract model-wide conclusions. Moreover, recent studies show that saliency-based methods may be invariant to the model or the data [11] and can be easily manipulated [10].

Intermediate discriminators Another trend is to probe the model with a dataset representative of some downstream task, either at a sentence level [2] or at a word level [33, 20]. The common practice is to train a classifier on top of selected intermediate features to assess their discriminative power. These approaches inspired our work, but rather than learning classifiers to solve downstream tasks, we probe the TM’s responses directly with a large set of concepts unrelated to the
final task. We propose treating the units of an already trained TM as classifiers themselves.

**Disentangled learning** Most methods tackling concept learning are based on training dedicated architectures. Concepts such as syntax and semantics [6], meaning and form [30], or sentiment and tense [17] can be disentangled by capturing different intrinsic aspects of text. Although effective, these methods suffer from the requirements of TM training. Our approach does not require training or knowledge of the training procedure. It requires only a pre-trained model and a dataset of concepts, such as the dataset described in Sec. 3.

3. **SentenceConcepts: A dataset of concepts represented by sentences**

We propose a data-driven approach to describe a concept. We collect $N_c^+$ positive sentences that contain concept $c$ and $N_c^-$ negative sentences that do not contain concept $c$. Such flexible definition allows diverse types of concepts to be represented. For example, one can collect positive sentences containing a keyword with a specific meaning, e.g. *note* as a reminder, or *note* as a musical frequency. We construct our dataset leveraging the recently published OneSec dataset [32], which contains sentences with one keyword annotated with a WordNet$^1$sense [26]. We consider 2 concept categories:

- **Sense**: Positive sentences contain a keyword with a specific WordNet sense, whereas negative sentences do not contain the keyword.
- **Homograph**: Positive sentences contain a keyword with a specific WordNet sense, whereas negative sentences contain the same keyword with a different meaning. Intuitively, *homograph* concepts are harder to disambiguate than *sense* concepts.

In total, the dataset contains 1344 *sense* and 297 *homograph* concepts. The complete list of concepts and details on the annotations are provided in Appendix E. The number of sentences collected is constrained by availability in the source dataset. We limit the data per concept to $N_c^+, N_c^- \in [100, 1000]$, randomly sampling when more than 1000 sentences are available.

4. **Expert Units**

4.1. **Finding expert units**

Let $x_i = [x_{i,1}, \ldots, x_{i,T}] \in \mathbb{R}^{D \times T}$ be a sentence composed of an arbitrary number $T$ of tokens $x_{i,t} \in \mathbb{R}^D$, with $D$ being the dimensionality of the token embedding. A layer $\ell$ of a TM produces an intermediate representation $z_i^\ell = [z_{i,1}^\ell, \ldots, z_{i,T}^\ell] \in \mathbb{R}^{D^\ell \times T}$, where typically $D^\ell$ is a multiple of $D$. Let $[u_{i,1}^{\ell}, \ldots, u_{i,T}^{\ell}]^\top = \text{maxpool}(z_{i,1}^\ell, \text{axis} = 1) \in \mathbb{R}^{D^\ell}$ be the intermediate representation max-pooled in the temporal dimension, where each element $u_{i,k}^{\ell} \in \mathbb{R}$ is the response of unit $k$ in layer $\ell$ to sentence $i$. For simplicity the $l(k)$ indexing is replaced by $m = 1..M$, with $M$ being the total number of units in the model. The layers analyzed are shown in Fig. 2. Let $u_{c,m}^m \in \mathbb{R}^{N_c}$ (where $N_c = N_c^+ + N_c^-$) be the pooled response of unit $m$ to the sentences that represent concept $c$, and let $b_c \in \mathbb{Z}_2^{N_c}$ be the binary labels for such sentences. We treat a unit as a binary classifier for the input sentences, and consider the whole network as a collection of binary classifiers. By using $u_{c,m}^m \in \mathbb{R}^{N_c}$ as prediction scores for $b_c$, we can compute $\text{AP}^c_m = \text{AP}(u_{c,m}^m, b_c) \in [0, 1]$ per unit $m$ and per concept $c$, which allows ranking units by expertise (or AP) on each concept. We expect that, given the large search space, certain classifiers will perform well on specific concepts: the expert units.

![Figure 2: Schema of a Transformer block](image-url)

In this work we analyze the units in the linear layers $A$, $\text{Aproj}$, $B$ and $\text{Bproj}$ in each block (red dots), where $D$ is the dimensionality of the embedding. For example, in GPT2-large ($D = 1280$ and 36 blocks) we analyze $36 \times 9D = 414720$ units.

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$^1$We adopt the WordNet sense key formulation, of the form `lemma%A:BB:CC`, clickable as web links across the paper.
4.2. Concept expertise $X_\gamma$

Let $\text{AP}_c^* = \max_m \{ \text{AP}_c^m \}$ be the AP of the best expert for concept $c$. Let $\gamma$ be the acquisition threshold so that a concept is considered as acquired in the model if $\exists \text{AP}_c^m \geq \gamma \forall m$ (or $\text{AP}_c^* \geq \gamma$). We define concept expertise as the percentage of concepts acquired by the model:

$$X_\gamma = \frac{| \{ c \text{ s.t. } \text{AP}_c^* \geq \gamma \} |}{|C|} \quad \forall c \in C. \quad \tag{1}$$

Finding an optimal $\gamma^*$ value  The choice of $\gamma$ is important to compute the concept expertise $X_\gamma$ in Eq. (1). The goal is to obtain an optimal $\gamma^*$ that produces an expertise representative of the generalization power of TMs. As a measure of generalization, we use the average performance of each model on typical downstream tasks: the 10 datasets composing GLUE with their different reported metrics [36] and SQuAD v1.1/2.0 [29, 28]. The reported performance is presented in Table 5 in Appendix B.

We measure the squared Pearson’s correlation coefficient $r^2$ between $X_\gamma$ and generalization. The obtained $\gamma^*$ tells the level of expertise required for a concept to be considered as acquired. We then define the optimal value of $\gamma$ as

$$\gamma^* = \arg\max_{\gamma} \left( \frac{1}{N_{\text{tasks}}} \sum_{\text{task}} r^2(X_\gamma, \text{task}) \right), \quad \tag{2}$$

with $\gamma \in [0.5, 1)$. To assess the robustness of $\gamma^*$, the tasks are randomly split into reference and test sets, with a ratio 60/40%. Next, we compute $\gamma^*$ for each subset, and we measure the RMSE between the obtained values on the reference and test set (10 random splits). We treat the sense and homograph concepts independently since they are fundamentally different. We obtain a $\gamma^* = 0.997$ with a RMSE of 0.0004 for concepts sense and $\gamma^* = 0.985$ with a RMSE of 0.0028 for concepts homograph. The low RMSE shows that the value of $\gamma^*$ generalizes well on disjoint sets of tasks. For simplicity, we express the optimal values as $\gamma^* = \{ \text{sense: } 0.997, \text{homograph: } 0.985 \}$, and we define the combined expertise as

$$X_{\gamma^*} = \frac{1}{N_{\text{concepts}}} \sum_{g \in \{\text{sense, homograph}\}} N_g X_{\gamma^*}^g. \quad \tag{3}$$

The high values of $\gamma^*$, together with the obtained $r^2 = 0.833$, suggest that the number of good and diverse experts in the model is correlated with its generalization power (see Table 2 for full results).

4.3. Results on expert units

All of the pre-trained models evaluated are obtained from the Huggingface Transformers repository [37].
version 2.1.1. More precisely, we analyze BERT-B/L [9], RoBERTa-S/L/LM [20], DistilBERT [31], GPT2-S/M/L [27] and XLM [19]. The sentences are tokenized using the default settings in the repository.

### 4.3.1 Concept distribution results

The distribution of acquired concepts per layer type is shown in Fig. 3 for models GPT2-L (I, II) and RoBERTa-L (III, IV). A concept is considered acquired in a layer $\ell$ if $\exists A|_{c(k,\ell)}^{\gamma} \geq \gamma$. In this experiment, we use $\gamma = 0.95$ for visualization purposes, $\gamma^\star$ being too restrictive.

We observe that shallow layers in TMs accumulate more concepts than deep layers. Within the Transformer blocks (see Fig. 2) in GPT2-L, B layers acquire about 3.5x more concepts than A layers and more than 10x than Aproj and Bproj layers. This suggests that the expanding layers (A and B) in the Transformer block are better at learning concepts at a unit level. RoBERTa-L produces a similar distribution of concepts, with A and B layers accumulating most of the concepts. Compared to GPT2-L, RoBERTa-L has a smaller drop in the number of concepts from shallow to deep layers. GPT2-L is a generative model composed of Transformer decoders, while RoBERTa is a stack of encoders. Our results show that generative architectures in NLP tend to accumulate concepts early in the model. Such an observation was reported by [3] in the image GAN domain, but to the best of our knowledge we report the first observation of this phenomenon in the NLP domain. Refer to Appendix A for results on other models.

### 4.3.2 Expertise and generalization results

**Concept expertise** The concept expertise obtained by the considered models is summarized in Table 1. RoBERTa-Lm is the model that achieves better combined expertise $\chi_{\gamma^\star} = 15.36\%$, followed by RoBERTa-L and GPT2-L, both with 12.92%. It is interesting to note that RoBERTa-L doubles the concept expertise of BERT only by modifying the training procedure and the data.

| Model         | Model size | $\chi_{\gamma}^{\text{sense}}$ | $\chi_{\gamma}^{\text{homograph}}$ | $\chi_{\gamma^\star}$ |
|---------------|------------|---------------------------------|--------------------------------------|------------------------|
| BERT-B        | 110M       | 1.04% (14)                      | 5.72% (17)                           | 1.89%                  |
| BERT-L        | 330M       | 7.51% (101)                     | 5.72% (17)                           | 7.19%                  |
| Distilbert    | 66M        | 3.65% (49)                      | 5.72% (17)                           | 4.02%                  |
| GPT2-S        | 117M       | 1.79% (24)                      | 1.35% (4)                            | 1.71%                  |
| GPT2-M        | 345M       | 3.65% (49)                      | 3.03% (9)                            | 3.53%                  |
| GPT2-L        | 774M       | 15.03% (202)                    | 3.37% (10)                           | 12.92%                 |
| RoBERTa-B     | 125M       | 1.71% (23)                      | 3.70% (11)                           | 2.07%                  |
| RoBERTa-L     | 355M       | 14.66% (197)                    | 5.05% (15)                           | 12.92%                 |
| RoBERTa-Lm    | 355M       | 17.86% (240)                    | 4.04% (12)                           | 15.36%                 |
| XLM           | 667M       | 9.30% (125)                     | 5.39% (16)                           | 8.59%                  |

| Model         | Model size | $\chi_{\gamma}^{\text{sense}}$ | $\chi_{\gamma}^{\text{homograph}}$ | $\chi_{\gamma^\star}$ |
|---------------|------------|---------------------------------|--------------------------------------|------------------------|
| BERT-B        | 110M       | 1.04% (14)                      | 5.72% (17)                           | 1.89%                  |
| BERT-L        | 330M       | 7.51% (101)                     | 5.72% (17)                           | 7.19%                  |
| Distilbert    | 66M        | 3.65% (49)                      | 5.72% (17)                           | 4.02%                  |
| GPT2-S        | 117M       | 1.79% (24)                      | 1.35% (4)                            | 1.71%                  |
| GPT2-M        | 345M       | 3.65% (49)                      | 3.03% (9)                            | 3.53%                  |
| GPT2-L        | 774M       | 15.03% (202)                    | 3.37% (10)                           | 12.92%                 |
| RoBERTa-B     | 125M       | 1.71% (23)                      | 3.70% (11)                           | 2.07%                  |
| RoBERTa-L     | 355M       | 14.66% (197)                    | 5.05% (15)                           | 12.92%                 |
| RoBERTa-Lm    | 355M       | 17.86% (240)                    | 4.04% (12)                           | 15.36%                 |
| XLM           | 667M       | 9.30% (125)                     | 5.39% (16)                           | 8.59%                  |

Table 1: Expertise for sense and homograph concepts, and combined expertise $\chi_{\gamma^\star}$. In parenthesis the actual number of concepts acquired. RoBERTa-Lm shows the highest $\chi_{\gamma^\star} = 15.36\%$. The models analyzed obtain a low homograph expertise $\chi_{\gamma}^{\text{homograph}} \leq 5.72\%$ compared to sense concepts.

We observe that sense concepts are acquired better than homograph concepts, as expected given the difficult disambiguation of the latter. In Fig. 3(I) we show the histogram of AP$_c^\star$ for all concepts. Note how many homograph concepts are not being detected, while almost all sense concepts are detected with AP$_c^\star > 0.90$. Building pre-trained models inherently able to disambiguate homograph concepts at unit level remains a challenge, and we speculate that such knowledge will help the models generalize even better.

In Fig. 4(II) we show the histogram of expert units that acquire a sense concept at $\gamma = 0.95$, for model RoBERTa-L. We observe that most of the concepts have less than 50 dedicated expert units (0.022%), with a median of 7 experts (0.0032%) per concept. Taking into account that 221184 units were analyzed for this model, we conclude that TMs dedicate very specific groups of experts to different concepts. The results in Sec. 6.1 show that these experts are causal.

**Generalization** In Table 2 we show that concept expertise $\chi_{\gamma^\star}$ in Eq. (3) is a robust measure of generalization of TMs, and can be used as a model evaluation metric rather than fine-tuning on downstream tasks. We report the squared Pearson’s correlation coefficient $r^2 \in [0, 1]$ of the linear regression between the performance of TMs on downstream tasks (see Sec. 4.2) versus $\chi_{\gamma^\star}$. Only the models reporting results are used in the correlation analysis. For comparison, we report in column (T) the average correlation between perfor-
Figure 4: (I) Histogram of the AP\textsuperscript{c} per concept for model RoBERTa-L. Most of \textit{sense} concepts are detected with AP\textsuperscript{c} > 0.90, while \textit{homograph} concepts present a wide range of AP\textsuperscript{c}. The vertical lines correspond to the values γ\textsuperscript{c} found in Sec. 4.2. (II) Histogram of the number of expert units that acquire a sense concept at γ = 0.95. Most of the concepts have less than 50 experts associated, a very low value (0.022%) compared to the 221184 units analyzed for RoBERTa-L showing that the number of experts per concept in a TM is very selective.

Table 2: Squared Pearson’s coefficient (r\textsuperscript{2}) of the linear regressions between the reported performance on various tasks versus the model size (S), the average versus all the other tasks (T) and the combined concept expertise Xγ\textsuperscript{c} (Eq. (3)). Only those models reporting results on each dataset are used (first column). On average, the correlation using Xγ\textsuperscript{c} (0.833) is better than the average correlation among all tasks (0.826), the latter requiring evaluation (involving fine-tuning) on all the tasks.

5. Concept overlap Ω

Recent works in image processing have shown that CNN filters can represent multiple concepts [3, 4, 11]. Based on this observation, we propose a method to explore co-learning of concepts by TMs in the NLP domain. We first set a threshold τ\textsubscript{c} = percentile\textsubscript{99} (AP\textsubscript{m}c) per concept, then we define s\textsubscript{c} = {1 if AP\textsubscript{m}c > τ\textsubscript{c} else 0} ∈ Z\textsuperscript{M} as our binary concept representation. Note that s\textsubscript{c} has elements with value 1 for the top 1% units classifying the concept. Let the overlap between concepts q and v be

\[ \Omega(q, v) = \frac{\|s_q \cap s_v\|_1}{\|s_q \cup s_v\|_1} \in [0, 1], \quad (4) \]

representing the number of top units that classify both concepts with high AP\textsubscript{m}c.

5.1. Concept overlap results

In Table 3 we show that concepts with related senses present a high overlap of top experts, evidencing concept co-learning. More precisely, we show the 5 concepts v with highest overlap Ω(q, v) (defined in Eq. (4))

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3With the exception of STS-(p), which shows 0.0 correlation with model size and a very poor correlation (0.49) with the other tasks too.
Table 3: Top-5 concepts in terms of expert overlap \( \Omega(q, v) \) (Eq. (4)) with a query concept for RoBERTa-L. The overlap shows the amount of top experts shared by two concepts \( q \) and \( v \). Even if the word representing the concept is the same (chair), the concepts overlapping are different and relate to the actual WordNet definition (click each concept for WordNet link), showing that the model takes the meaning into account. Concepts marked with ‘VS.’ are homograph concepts.

| Query definition | Concept | \( \Omega(q, v) \) |
|------------------|---------|------------------|
| A seat for one person, with a support for the back. | chair%1:06:00 (query) | 1.000 |
|                  | table%1:06:01 | 0.458 |
|                  | bed%1:06:00  | 0.361 |
|                  | cup%1:06:00  | 0.341 |
|                  | table%1:06:01 VS. table%1:14:00 | 0.336 |
|                  | floor%1:06:00 | 0.328 |
| The position of professor. | chair%1:04:00 (query) | 1.000 |
|                  | chair%1:04:00 VS. chair%1:06:00 | 0.575 |
|                  | fellow%1:18:02 | 0.371 |
|                  | director%1:18:03 | 0.297 |
|                  | administration%1:04:00 | 0.243 |
|                  | member%1:18:00 | 0.241 |

6. Inducing concepts in pre-trained Language Models

Language Models (LMs) are generative models able to generate text consistent with linguistic rules. More formally, LMs learn the probability of a generated sentence \( x \) as \( p(x) = p(x_1, \ldots, x_T) = \prod_{k=1}^{T} p(x_k|x_{<k}) \).

A conditional generative model maximizes the joint distribution \( p(x, y) = p(y|x)p(x) \), where \( x \) is the generated sentence and \( y \) is a latent conditional variable (i.e. a specific concept in \( x \)). As proposed by [14], this equation can be interpreted as a product of experts. The same interpretation was adopted by [23] for conditioned image generation. We adapt Hinton’s and Nguyen’s interpretation to the case of conditioned text generation, where \( p(y|x) \) is an expert that determines the condition for generation, and \( p(x) \) is an expert ensuring that the generated sequence lies within the manifold of sentence distributions. Typically we do not sample jointly \( x \) and \( y \), we rather define a condition \( y = c \) beforehand (e.g. the concept) and sample \( x \). Thus one can write:

\[
p(x|y = c) \propto p(y = c|x)p(x). \tag{5}
\]

As opposed to [23] that models \( p(y = c|x) \) with an external network, we hypothesize that the condition expert \( p(y = c|x) \) already exists within the same model, and that the model is able to maximize \( p(x|y = c) \) by trusting its internal condition expert. Such intuition is based on recent findings in neuroscience [22] that show that the human brain increasingly trusts selective groups of neurons as it learns. If we can identify the parts of the model that contribute to the condition expert \( p(y = c|x) \), we could control the amount of concept \( c \) in the generated sentences. The quality of the experts for a given concept will dictate the extent to which such concept can be controlled during generation.

As explained in Sec. 4.1, \( AP^m_c \) explains how well unit \( m \) is able to classify concept \( c \). We consider those units with high \( AP^m_c \) as internal condition experts for concept \( c \), each accumulating evidence in \( p(y = c|x) \). To control \( p(y = c|x) \) we force the top-K experts to be active. The larger \( K \), the more concept \( c \) will be present in the output, provided that the expert has learnt the concept. Too large \( K \) will result in illegible sentences, since \( p(y = c|x) \) will dominate \( p(x) \) in Eq. (5).

The proposed forcing strategy is inspired by [4], where the authors compute the mean filter response conditioned to the presence of some object in a GAN output image. We adapt their approach to the LM case: (1) we cannot quantify the presence of \( c \), however the output and the input of LMs are tightly related given the sequential decoding, which allows the forcing value to be computed as the median active value when concept \( c \) is present in the input (not the output); (2) our quantification strategy is by \( AP^m_c \) given a binary dataset, while [4] consider CNN filter responses as segmentation masks to compute IOU with a labeled image.

The results in Sec. 6.1 confirm our hypothesis that conditional experts exist in the model, and that the model leverages them to condition generation. Further
Table 4: Examples of generated sentences using GPT2-L with initial context Once upon a time, sorted by the number of top experts for different WordNet concepts. In parenthesis the percentage of experts forced out of the total 414720 units analyzed. For concept *bird*%1:05:00, the presence of the concept increases as we force more experts, empirically proving the impact of expert forcing on \( p(y = c|x) \) in (5). The percentage of experts required is extremely low, saturating at 200 experts (0.048%) in this example, where \( p(y = c|x) \) already dominates \( p(x) \) in (5). We also show generated sentences for concepts *lead*%1:07:02 and *lead*%1:27:00, showing the model’s ability to capture the meaning of the concept.

| K forced | Generated induced for concept *bird*%1:05:00 (warm-blooded egg-laying vertebrates) |
|----------|-----------------------------------------------------------------------------------|
| 0 (0%)   | I had a friend who used to teach high school English and he was like, “Oh, all you have to do is just get out there |
| 40 (0.009%) | many of these treasures were worth hundreds of thousands of dollars. in But this isn’t the first time that a horse has been |
| 60 (0.015%) | through a freak occurrence, an invasion of house sparrows, which so often reduces the black-browed this nation recreats through |
| 80 (0.019%) | our own ancestors rode about on chicken-like air wings. in But this wonder of the air has no such wings. in Taking down |
| 200 (0.048%) | of year, birds chase each and watching. flat racing form, bird, bird bird bird bird bird bird bird bird bird Bird |

| Once upon a time + Generated induced for concept *lead*%1:07:02 (an advantage held by a competitor in a race) |
| 50 (0.012%) | the left-hander would always start at the front in the first two instances, but when Mauricio Gaponi rose to the podium, |

| Once upon a time + Generated induced for concept *lead*%1:27:00 (a soft heavy toxic malleable metallic element) |
| 100 (0.024%) | a crust layer was applied to a partially fortified nickel base, thereby causing to zinc- and copper- ground element cob. The occurrence of those metal and chrome |

6.1. Results on conditioned text generation

Expert units can be used beyond model evaluation. In this experiment, we use experts units for text generation. The objective is threefold: (1) to demonstrate that ranking units by \( AP^m_c \) is a suitable strategy to find the experts for concept \( c \); (2) to prove expert units are causal in the setting of LM, empirically showing that we can control \( p(y = c|x) \) in Eq. (5); and (3) to show that LMs can be conditioned without training or using additional parameters. Table 4 illustrates the generation of sentences using GPT2-L while forcing the top-K experts for WordNet concept *bird*%1:05:00 as explained in Sec. 6. The decoding strategy is by nucleus filtering with \( p = 0.9 \) [15]. We observe how the presence of the concept gradually increases as we increase K, and that it saturates at about 200 experts forced. This result empirically explains Eq. (5), showing that K controls \( p(y = c|x) \) until saturation, when the effect of \( p(x) \) (generate plausible sentences) is not evident anymore. The number of experts forced is extremely low, saturating at 200 experts (or 0.048% of the 414720 units analyzed for GPT2-L), showing how LMs dedicate very selective units to specific concepts. This result draws a parallelism between the behavior of TMs and that of human brains [22]. Extended results in Appendix D.

7. Limitations of the method

On the data We have proposed a data-driven approach, thus being limited to the presented data. The proposed dataset in Sec. 3 is weakly annotated, and there are inconsistencies inherent in the source OneSec dataset. The more diverse and accurate the concept dataset, the better it will help evidence the generalization power of TMs.

On individual expert units We have shown that individual expert units can be interpreted as experts for specific concepts, specially in the sense category. It is possible, but not yet explored, that more complex concepts such as homograph, require a more complex expert such as a set of units.

On the compute requirements Finding experts in TMs (Sec. 4.1) is an exhaustive task that implies some memory and compute requirements. A forward pass over the dataset is required and is the most demanding step. The proposed dataset in Sec. 3 consists of 1641 concepts with an average of 1.5K sentences each, thus
\[ \sim 2.5M \] sentences. According to the benchmark in the Transformers repository, the average GPU inference time for BERT-B for sentences of 128 tokens is 9ms, which translates into 6.15 hours for the whole dataset. Our method can be parallelized per concept, thus with 8 GPUs the total time is reduced to 45 minutes. The computed \( \text{AP}_c^{m} \forall m, c \) requires, in the GPT2-L case, \( 414720 \times 1641 \) floats \( \approx 2.5 \text{GB} \) plus overhead, such as unit naming. For comparison, a single evaluation of BERT-B on SQuAD v1.1 takes 24min. But several evaluations are required for hyper-parameter tuning and statistical significance. Summing up, evaluating on SQuAD v1.1/2.0 plus all GLUE tasks is more demanding than our proposed evaluation.

8. Conclusions

We have defined expert units in the context of TMs and proposed a method to identify and rank them with respect to a specific concept. Our results show that generalization of TMs is related to the presence of both diverse and high-performant experts. We also have shown how the top experts for different concepts can be used to analyze concept co-learning, and how this co-learning can be used for concept explainability. In addition, we have proposed a method to condition the output of language models by forcing its top experts identified for a concept. Such conditioning is applied to pre-trained models, without requiring re-training or using additional parameters, leveraging the actual model knowledge. A parallelism between the presence of expert units in TMs and the presence of specialized filters in image processing CNNs/GANs has been suggested, as well as with the presence of specialized structures in the human brain. Our findings open new avenues of research, such as conditioning language models on their own knowledge or improving training leveraging the presence of experts.

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Appendices

A. Concept distribution for all models considered

Figure 5: Concept distribution per layer at $\gamma = 0.95$ for model DistilBERT.

Figure 6: Concept distribution per layer at $\gamma = 0.95$ for model BERT-B.

Figure 7: Concept distribution per layer at $\gamma = 0.95$ for model BERT-L.
Figure 8: Concept distribution per layer at $\gamma = 0.95$ for model GPT2-S.

Figure 9: Concept distribution per layer at $\gamma = 0.95$ for model GPT2-M.

Figure 10: Concept distribution per layer at $\gamma = 0.95$ for model RoBERTa-Lm.
Figure 11: Concept distribution per layer at $\gamma = 0.95$ for model XLM.
B. Performance of the considered models on downstream tasks

| Model      | BERT-B | BERT-L | Distilbert | RoBERTa-L | XLM   |
|------------|--------|--------|------------|-----------|-------|
| Model size | 110M   | 330M   | 66M        | 355M      | 667M  |
| GLUE Score | 78.3   | 80.5   | 76.8       | 88.5      | 83.1  |
| CoLA       | 52.1   | 60.5   | 49.1       | 67.8      | 62.9  |
| SST-2      | 93.5   | 94.9   | 92.7       | 96.7      | 95.6  |
| MRPC (acc) | 88.9   | 89.3   | 90.2       | 92.3      | 90.7  |
| MRPC (F1)  | 84.8   | 85.4   | 89.8       | 87.1      |       |
| STS-B (p)  | 87.1   | 87.6   | 90.7       | 92.2      | 88.8  |
| STS-B (s)  | 85.8   | 86.5   | -          | 91.9      | 88.2  |
| QQP (acc)  | 71.2   | 72.1   | -          | 74.3      | 73.2  |
| QQP (F1)   | 89.2   | 89.3   | 89.2       | 90.2      | 89.8  |
| MNLI-m     | 84.6   | 86.7   | 81.8       | 90.8      | 89.1  |
| MNLI-mm    | 83.4   | 85.9   | -          | 90.2      | 88.5  |
| QNLI       | 90.5   | 92.7   | 90.2       | 98.9      | 94    |
| RTE        | 66.4   | 70.1   | 62.9       | 88.2      | 76    |
| WNLI       | 65.1   | 65.1   | 44.4       | 89        | 71.9  |
| AX         | 34.2   | 39.6   | -          | 48.7      | 44.7  |
| SQuAD 1.1 (F1) | 88.5 | 91.5   | 86.9       | 94.6      | -     |
| SQuAD 2.0 (F1) | 76.3 | 85.81  | -          | 89.8      | -     |

Table 5: Performance of the considered models on various downstream tasks, as reported in the reference papers. Not all models report performance on all tasks.
C. Concept co-learning extended results

| Concept            | Type     | Overlap | WordNet definition                                                                 |
|--------------------|----------|---------|-----------------------------------------------------------------------------------|
| chair%1:06:00      | sense    | 1.000   | a seat for one person, with a support for the back                                  |
| table%1:06:00      | sense    | 0.458   | a piece of furniture having a smooth flat top that is usually supported by one or   |
| bed%1:06:00        | sense    | 0.361   | a piece of furniture that provides a place to sleep                                |
| table%1:06:00      | homograph| 0.336   | a piece of furniture having a smooth flat top that is usually supported by one or   |
| floor%1:06:00      | sense    | 0.328   | the inside lower horizontal surface (as of a room, hallway, tent, or other structure) |
| chair%1:04:00      | sense    | 1.000   | the position of professor                                                          |
| chair%1:04:00      | homograph| 0.575   | the position of professor VS. a seat for one person, with a support for the back     |
| director%1:18:03   | sense    | 0.297   | member of a board of directors                                                    |
| administration%1:04:00 | sense | 0.243   | a method of tending to or managing the affairs of a some group of people (especially the group’s business affairs) |
| member%1:18:00     | sense    | 0.241   | one of the persons who compose a social group (especially individuals who have joined and participate in a group organization) |
| suspension%1:26:00 | sense    | 1.000   | a time interval during which there is a temporary cessation of something            |
| suspension%1:26:00 | homograph| 0.522   | a time interval during which there is a temporary cessation of something VS. a mixture in which fine particles are suspended in a fluid where they are supported by buoyancy |
| recovery%1:11:00   | sense    | 0.398   | a period of the year marked by special events or activities in some field          |
| season%1:28:02     | sense    | 0.387   | the possibility of future success                                                  |
| prospect%1:26:00   | sense    | 0.380   | earnest and conscientious activity intended to do or accomplish something         |
| suspension%1:27:00 | sense    | 1.000   | a mixture in which fine particles are suspended in a fluid where they are supported by buoyancy |
| solution%1:2:7:00  | sense    | 0.492   | a homogeneous mixture of two or more substances; frequently (but not necessarily) a liquid solution |
| deposit%1:19:00    | sense    | 0.438   | the phenomenon of sediment or gravel accumulating                                  |
| material%1:23:00   | sense    | 0.432   | the tangible substance that goes into the makeup of a physical object              |
| powder%1:2:7:00    | sense    | 0.415   | a solid substance in the form of tiny loose particles, a solid that has been pulverized |
| crystal%1:27:00    | sense    | 0.413   | a solid formed by the solidification of a chemical and having a highly regular atomic structure |
| phone%1:06:00      | sense    | 1.000   | electronic equipment that converts sound into electrical signals that can be transmitted over distances and then converts received signals back into sounds |
| subscriber%1:18:01 | sense    | 0.423   | someone who contracts to receive and pay for a service or a certain number of issues of a publication |
| talk%1:10:00       | sense    | 0.344   | an exchange of ideas via conversation                                             |
| need%1:13:00       | homograph| 0.328   | anything that is necessary but lacking VS. a condition requiring relief            |
| message%1:10:00    | sense    | 0.320   | a communication (usually brief) that is written or spoken or signaled              |
| phone%1:10:00      | sense    | 1.000   | (phonetics) an individual sound unit of speech without concern as to whether or not it is a phoneme of some language |
| phone%1:10:00      | homograph| 0.412   | (phonetics) an individual sound unit of speech without concern as to whether or not it is a phoneme of some language VS. electronic equipment that converts sound into electrical signals that can be transmitted over distances and then converts received signals back into sounds |
| letter%1:10:01     | sense    | 0.362   | the conventional characters of the alphabet used to represent speech              |
| american%1:10:00   | homograph| 0.335   | the English language as used in the United States VS. a native or inhabitant of the United States |
| word%1:10:00       | sense    | 0.330   | a unit of language that native speakers can identify                              |
| form%1:10:00       | sense    | 0.297   | the phonological or orthographic sound or appearance of a word that can be used to describe or identify something |

Table 6: Top-5 concepts co-learnt with a query sense concept (represented by an overlap of 1.0) for model RoBERTa-L. Observe how the concepts that maximally overlap with each query are strongly related with the definition of the query, even when the word representing the query is the same.
Table 7: Example of sense concepts that have similar meanings (model RoBERTa-L). Both query concepts are represented by the word market, but they overlap strongly with the other query concept. Actually, the homograph concept market%1:04:00 VS. market%1:14:00 achieves a low APc = 0.523.

Table: Concept Type Overlap WordNet definition

| Concept   | Type    | Overlap | Definition                                                                 |
|-----------|---------|---------|-----------------------------------------------------------------------------|
| market%1:04:00 | sense   | 1.000   | the world of commercial activity where goods and services are bought and sold |
| economy%1:14:00 | sense   | 0.388   | the system of production and distribution and consumption                     |
| market%1:14:00 | sense   | 0.353   | the customers for a particular product or service                             |
| capital%1:21:01 | sense   | 0.349   | assets available for use in the production of further assets                 |
| labor%1:14:00  | sense   | 0.304   | a social class comprising those who do manual labor or work for wages        |
| wealth%1:26:00 | sense   | 0.267   | the state of being rich and affluent; having a plentiful supply of material   |
| goods and money |

leader%1:06:00 VS. market%1:04:00 homograph 0.208 the customers for a particular product or service VS. the world of commercial activity where goods and services are bought and sold

leader%1:06:00 sense 0.198 a featured article of merchandise sold at a loss in order to draw customers

Figure 12: t-SNE projection of the concept representations sc proposed in Sec. 5. Zoom-in on concepts chair%1:04:00 and chair%1:06:00, whose meaning can easily be explained by their neighbors. The t-SNE projection is an alternative view of the nearest neighbor results shown in Table 6. In orange homograph concepts.
Figure 13: t-SNE projection of the concept representations $s_c$ proposed in Sec. 5. Zoom-in on concepts right%1:07:00 and right%1:15:00, whose meaning can easily be explained by their neighbors. In orange homograph concepts.
D. Conditioned generation extended results

Table 8: Extended results on successful conditioned generation. All the concepts shown have an $\text{AP}^*_c \geq \gamma^*$. We borrow the context from the OpenAI GPT2 work [27].

| K forced | WordNet concept | $\text{AP}^*_c$ | Context + Generated (conditioned to concept) |
|----------|----------------|----------------|------------------------------------------------|
| 60       | elevator%1:06:00 | 0.9999         | In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English. The two scientists were unable to solve a problem in their research when they started a great deal of unusual levitation and deceleration, which blew them up a few hundred feet and dropped them back to the ground. |
| 60       | smoke%1:19:00    | 0.9999         | In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English. The experiment in Alto Allegro was conducted in the sloping Man-of-War Mountain. This was a truly historic event! Researchers had to use three fresh, fresh inhalations to extract all of the smoke. The study has been approved by the Spanish government |
| 60       | gold%1:21:00     | 0.9996         | In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English. Our researcher found the magical 'Slab Silver', which is one of the most outstanding forms of gold we have ever had our eyes on. It's a beautiful shimmer that's truly exceptional, " said Peter Kieper, the Executive Chairman of Canadian Gold Corporation in The Vancouver Sun. |
| 60       | frustration%1:12:00 | 0.9984      | In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English. Even though we had spent a lot of time just to find the path that could lead to the species, we did not have success, " has an Indian scientist, taking measurements from a lone unicorn on the walls of a remote mountain, wearing brightly red patches of clothing. |
| 60       | retirement%1:26:00 | 0.9981       | In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English. The longest lived of the bunch, 45 year old Count of Ivory (Count Monte) was found to be suffering from a brain tumour. Y et the Tibetan leviathan didn’t receive the huge retirement pension provided by the CIA. He died peacefully at the age of 75 in April in a spa |

Table 9: Extended results on unsuccessful conditioned generation. The concept has $\text{AP}^*_c \ll \gamma^*$, and we observe how the model struggles to produce legible sentences.
E. Concept list

The sense concepts considered are listed in Tables 10, 11, 12, 13 and homograph concepts in Table 14. Concepts are sorted by the AP\textsuperscript{c} obtained by GPT2-L, to illustrate how concepts are acquired.

Note that the meaning of the concept is important. For example, concept one\%1:23:00 (the smallest whole number or a numeral representing this number, e.g. "he has the one but will need a two and three to go with it"; "they had lunch at one") achieves a AP\textsuperscript{c} = 0.9885, while concept one\%1:09:00 (a single person or thing, e.g. "he is the best one"; "this is the one I ordered") only achieves AP\textsuperscript{c} = 0.8779.

Details on the annotations Each sentence in the OneSec dataset [32] is annotated as in the following example:

```xml
<instance docsrc="Indigenous architecture" id="shelter.00002">
  <answer instance="shelter.00002" senseid="shelter%1:06:00::" />
  <context>
    Types There are three traditional types of igloos , all of different sizes and used for different purposes. The smallest were constructed as temporary
    <head>shelters</head>, usually only used for one or two nights .
  </context>
</instance>
```

The senseid label is the one of the marked word (shelters in this example, between <head> and </head>). We use the senseid as follows. The part before the % is called lemma, while the remaining numbers uniquely identify the concept in WordNet. We parse all the sentences for a given senseid to create the positive sentences of each concept, only keeping those senseid with more than 100 sentences. As explained in Sec. 3 the negative sentences of sense concepts are randomly selected from all the senseid with different lemma than the positive ones, while the negative sentences of the homograph concepts are those with different senseid but same lemma.
| AP* sense concept | AP* sense concept | AP* sense concept |
|-------------------|-------------------|-------------------|
| 0.9541 word%1.10:03 | 0.9370 leader%1.06:00 | 0.9168 research%1.09:00 |
| 0.9540 joint%1.18:01 | 0.9366 character%1.18:01 | 0.9167 case%1.10:00 |
| 0.9538 study%1.10:00 | 0.9366 character%1.18:00 | 0.9167 case%1.10:00 |
| 0.9536 spam%1.04:06 | 0.9366 character%1.26:02 | 0.9159 sure%1.18:00 |
| 0.9534 count%1.03:03 | 0.9355 community%1.21:00 | 0.9155 safe%1.14:00 |
| 0.9532 nation%1.18:01 | 0.9341 share%1.97:01 | 0.9153 share%1.11:01 |
| 0.9530 nation%1.07:00 | 0.9338 paper%1.21:00 | 0.9149 story%1.07:00 |
| 0.9530 share%1.18:01 | 0.9336 share%1.07:00 | 0.9145 change%1.22:00 |
| 0.9518 twitter%1.18:00 | 0.9333 company%1.41:03 | 0.9116 case%1.10:00 |
| 0.9515 education%1.09:00 | 0.9333 statement%1.23:02 | 0.9109 executive%1.07:00 |
| 0.9514 name%1.28:00 | 0.9323 sense%1.01:00 | 0.9099 tweet%1.10:00 |
| 0.9514 name%1.28:00 | 0.9312 apple%1.27:00 | 0.9085 media%1.04:00 |
| 0.9506 nation%1.18:01 | 0.9310 regard%1.09:01 | 0.9054 anti%1.07:00 |
| 0.9506 nation%1.18:01 | 0.9305 case%1.18:00 | 0.9051 expansion%1.03:01 |
| 0.9502 example%1.07:06 | 0.9299 relation%1.04:03 | 0.9049 system%1.14:00 |
| 0.9502 nation%1.18:01 | 0.9293 trace%1.11:00 | 0.9009 trace%1.23:00 |
| 0.9498 view%1.09:02 | 0.9292 performance%1.04:01 | 0.8978 careers%1.06:01 |
| 0.9498 view%1.09:02 | 0.9290 america%1.17:00 | 0.8977 government%1.04:00 |
| 0.9495 opponent%1.18:01 | 0.9283 trace%1.10:00 | 0.8976 media%1.10:00 |
| 0.9495 opponent%1.18:01 | 0.9282 trace%1.10:00 | 0.8951 trace%1.10:00 |
| 0.9494 case%1.11:00 | 0.9280 trace%1.09:01 | 0.8950 trace%1.09:00 |
| 0.9493 manage%1.11:00 | 0.9276 trace%1.14:00 | 0.8939 trace%1.28:00 |
| 0.9493 trace%1.11:00 | 0.9274 trace%1.14:00 | 0.8938 trace%1.14:00 |
| 0.9484 case%1.11:00 | 0.9271 trace%1.20:00 | 0.8928 service%1.09:00 |
| 0.9477 management%1.44:00 | 0.9268 trace%1.27:00 | 0.8926 media%1.09:00 |
| 0.9469 name%1.10:01 | 0.9263 management%1.24:00 | 0.8867 service%1.09:00 |
| 0.9467 nation%1.10:00 | 0.9257 nation%1.20:00 | 0.8861 service%1.09:00 |
| 0.9466 nation%1.10:00 | 0.9255 nation%1.28:02 | 0.8790 service%1.12:01 |
| 0.9464 constituent%1.07:01 | 0.9255 nation%1.09:01 | 0.8787 nation%1.10:00 |
| 0.9461 constituent%1.18:00 | 0.9254 nation%1.28:00 | 0.8779 nation%1.19:00 |
| 0.9457 share%1.18:00 | 0.9252 nation%1.18:03 | 0.8734 nation%1.19:00 |
| 0.9457 share%1.18:00 | 0.9250 nation%1.18:03 | 0.8732 nation%1.19:01 |
| 0.9453 example%1.19:02 | 0.9246 nation%1.13:00 | 0.8693 nation%1.18:01 |
| 0.9454 nation%1.11:00 | 0.9246 nation%1.11:01 | 0.8668 nation%1.10:01 |
| 0.9447 example%1.09:02 | 0.9243 nation%1.09:01 | 0.8640 nation%1.10:00 |
| 0.9438 type%1.11:00 | 0.9226 nation%1.25:00 | 0.8637 national%1.10:00 |
| 0.9435 nation%1.09:01 | 0.9225 nation%1.11:00 | 0.8582 national%1.10:00 |
| 0.9425 member%1.24:00 | 0.9224 reference%1.10:00 | 0.8578 national%1.09:01 |
| 0.9421 target%1.10:00 | 0.9220 recommendation%1.03:00 | 0.8508 nation%1.06:00 |
| 0.9420 expert%1.28:00 | 0.9218 recommendation%1.20:00 | 0.8481 nation%1.10:01 |
| 0.9416 assembly%1.04:02 | 0.9217 review%1.06:00 | 0.8478 nation%1.18:00 |
| 0.9414 research%1.07:00 | 0.9206 recommendation%1.09:01 | 0.8242 nation%1.28:00 |
| 0.9413 nation%1.11:00 | 0.9206 recommendation%1.13:00 | 0.8198 nation%1.12:00 |
| 0.9390 insurance%1.04:00 | 0.9203 place%1.15:00 | 0.8151 nation%1.12:00 |
| 0.9387 nation%1.21:00 | 0.9197 investigation%1.04:00 | 0.7439 nist%1.28:00 |
| 0.9386 investigation%1.09:00 | 0.9190 nation%1.28:00 | 0.7407 nation%1.28:00 |
| 0.9385 character%1.07:00 | 0.9190 nation%1.09:01 | 0.7407 nation%1.28:00 |
| 0.9384 group%1.2:00 | 0.9189 country%1.15:00 | 0.7407 nation%1.28:00 |
| 0.9380 nation%1.18:00 | 0.9180 nation%1.18:00 | 0.7407 nation%1.28:00 |
| 0.9374 apple%1.06:01 | 0.9168 nation%1.10:00 | 0.7407 nation%1.28:00 |

Table 13: List of *sense* concepts considered (4/4), sorted by the AP* obtained by GPT2-L.
