Finding Experts in Transformer Models

Xavier Suau Luca Zappella Nicholas Apostoloff {xsuaucuadros, lzappella, napostoloff}@apple.com Apple

Abstract

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 concept with a given average precision, where a concept is represented by a binary set of sentences containing the concept (or not). Leveraging the OneSec dataset [32], we compile a dataset of 1641 concepts that allows diverse expert units in TMs to be discovered. We show that expert units are important in several ways: (1) The presence of expert units is correlated ($r^2 = 0.833$) with the generalization power of TMs, which allows ranking TMs without requiring fine-tuning on suites of downstream tasks. We further propose an empirical method to decide how accurate such experts should be to evaluate generalization. (2) The overlap of top experts between concepts provides a sensible way to quantify concept co-learning, which can be used for explainability of unknown concepts. (3) We show how to self-condition off-the-shelf pre-trained language models to generate text with a given concept by forcing the top experts to be active, without requiring re-training the model or using additional parameters.

1. Introduction

Natural language processing (NLP) has evolved at a fast pace during recent years. Large and powerful models based on the Transformer architecture [35] can now be trained on large datasets, achieving impressive performance on many NLP tasks, such as GLUE [36] or SQuAD [29, 28]. Training TMs is tedious due to both the size of models and datasets, and requires resources that are unavailable to many users. For example, in [25]

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%1:04:00¹ 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 the term 'TM' appears in a sporting sense, and how TMs 'specialize', taking the initial context also into account.

the model was trained on 512 GPUs. A recent trend is to pre-train these large models on diverse datasets and make them available to the community [16, 9, 27, 19, 38, 21, 31], so that end-users can leverage the powerful features learnt to solve downstream tasks.

However, it is not fully understood why these models perform so well. Inspired by observations in neuroscience stating that the human brain is a network of hierarchically organized specialized modules [13] and that neurons become more selective as humans learn [22], we aim to find specialized modules in TMs, the

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 withoutfine-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. 1 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 keystone 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 [7]. 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 [1] 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, 8] 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 WordNet¹ 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

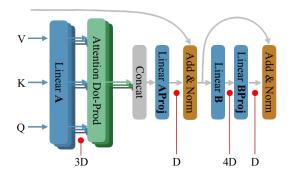


Figure 2: Schema of a Transformer block [35]. In this work we analyze the units in the linear layers A, Aproj, B and Bproj in each block (red dots), where D is the dimensionality of the embedding. For example, in GPT2-large (D=1280 and 36 blocks) we analyze $36\cdot 9D=414720$ units.

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 $oldsymbol{x}_i = [oldsymbol{x}_{i,1}, \cdots, oldsymbol{x}_{i,T}] \in \mathbb{R}^{D imes T}$ 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 ℓ of a TM produces an intermediate representation $\pmb{z}_i^\ell = [\pmb{z}_{i,1}^\ell, \cdots, \pmb{z}_{i,T}^\ell] \in$ $\mathbb{R}^{D^{\ell}\times T},$ where typically D^{ℓ} is a multiple of D. Let $[u_i^{(\ell,1)},\cdots,u_i^{(\ell,D^\ell)}]^{\top}=\operatorname{maxpool}(\boldsymbol{z}_i^{\ell},\operatorname{axis}=1)\in$ $\mathbb{R}^{D^{\ell}}$ be the intermediate representation max-pooled in the temporal dimension, where each element $u_i^{(\ell,k)} \in \mathbb{R}$ is the response of unit k in layer ℓ 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 $u_c^m \in \mathbb{R}^{N_c}$ (where $N_c = N_c^+ + N_c^-$) be the pooled response of unit m to the sentences that represent concept c, and let $\boldsymbol{b}_c \in \mathbb{Z}_2^{N_c}$ 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 $oldsymbol{u}_c^m \in \mathbb{R}^{N_c}$ as prediction scores for \boldsymbol{b}_c , we can compute $AP_c^m = AP(\boldsymbol{u}_c^m, \boldsymbol{b}_c) \in [0, 1]$ 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.

 $^{^1}$ We adopt the WordNet sense key formulation, of the form lemma %A:BB:CC, clickable as web links across the paper.

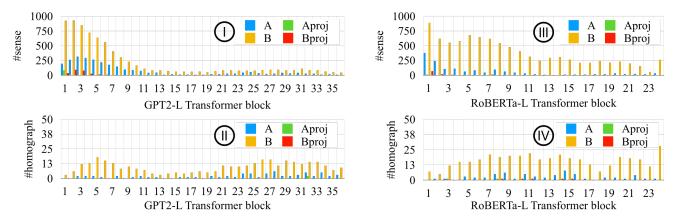


Figure 3: Number of acquired concepts ($\gamma=0.95$) per layer type for model GPT2-L (I, II) and RoBERTa-L (III, IV). Shallow layers acquire more *sense* concepts than deep layers, such effect being emphasized in GPT2-L. This behavior is similar to the one observed by [4] for image GANs. We further observe that B layers acquire 3.5x more concepts than A layers. Aproj and Bproj layers acquire very few concepts, suggesting that the expanding layers (A, B) in the Transformer block (Fig. 2) are more prone to learn concepts. *Homograph* concepts (II, IV) are spread across the layers, few being detected in the first Transformer blocks.

4.2. Concept expertise \mathcal{X}_{γ}

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

$$\mathcal{X}_{\gamma} = \frac{\left| \left\{ c \text{ s.t. } AP_c^{\star} \ge \gamma \right\} \right|}{|C|} \quad \forall c \in C.$$
 (1)

Finding an optimal γ^* value The choice of γ is important to compute the concept expertise \mathcal{X}_{γ} in Eq. (1). The goal is to obtain an optimal γ^* 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 \mathcal{X}_{γ} and generalization. The obtained γ^{\star} tells the level of expertise required for a concept to be considered as acquired. We then define the optimal value of γ as

$$\gamma^{\star} = \underset{\gamma}{\operatorname{argmax}} \left(\frac{1}{N_{\text{tasks}}} \sum_{\text{task}} r^{2}(\mathcal{X}_{\gamma}, \text{task}) \right), \quad (2)$$

with $\gamma \in [0.5,1)$. To assess the robustness of γ^* , the tasks are randomly split into reference and test sets, with a ratio 60/40%. Next, we compute γ^* 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 γ^* 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

$$\mathcal{X}_{\gamma^{\star}} = \frac{1}{N_{\text{concepts}}} \sum_{g \in (\text{sense, homograph})} N_g \mathcal{X}_{\gamma = \gamma^{\star}[g]}^{\text{g}}. \tag{3}$$

The high values of γ^* , 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 analyze²: 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 ℓ if $\exists \operatorname{AP}_c^{(k,\ell)} \geq \gamma$. In this experiment, we use $\gamma = 0.95$ for visualization purposes, γ^* 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 [4] 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 $\mathcal{X}_{\gamma^*}=15.36\%$, 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	$\mathcal{X}_{\gamma=0.997}^{\mathrm{sense}}$	$\mathcal{X}_{\gamma=0.985}^{ ext{homograph}}$	$\mathcal{X}_{\gamma^{\star}}$
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 \mathcal{X}_{γ^*} (3). In parenthesis the actual number of concepts acquired. RoBERTa-Lm shows the highest $\mathcal{X}_{\gamma^*} = 15.36\%$. The models analyzed obtain a low *homograph* expertise $\mathcal{X}_{\gamma}^{\text{homograph}} \leq 5.72\%$ 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. 4.(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 how that these experts are causal.

Generalization In Table 2, we show that concept expertise \mathcal{X}_{γ^*} 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 \mathcal{X}_{γ^*} . Only the models reporting results are used in the correlation analysis. For comparison, we report in column (T) the average correlation between perfor-

²The corresponding names in the transformers repository are: bert-base/large-cased, roberta-base/large/large-mnli, distilbert-base-uncased, gpt2-∅/medium/large and xlm-mlm-en-2048.

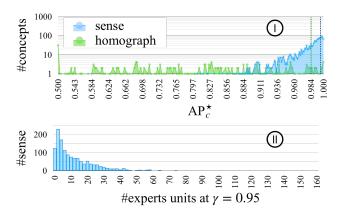


Figure 4: (I) Histogram of the AP_c^{\star} per concept for model RoBERTa-L. Most of *sense* concepts are detected with $AP_c^{\star} > 0.90$, while *homograph* concepts present a wide range of AP_c^{\star} . The vertical lines correspond to the values γ^{\star} found in Sec. 4.2. (II) Histogram of the number of expert units that acquire a *sense* concept at $\gamma = 0.95$. 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.

mance on a task with all the other tasks, as well as the correlation of downstream performance with the model size in column (S). We observe that \mathcal{X}_{γ^*} is strongly correlated with the performance on downstream tasks $(r^2>0.833)$, which is higher than the average correlation among tasks (0.826), the latter requiring evaluation (involving fine-tuning) on all the tasks. The correlation with \mathcal{X}_{γ^*} is better than the correlation between tasks for 12 of the 16 metrics used.

We further see that model size is not a metric that generalizes well, since it correlates strongly with the perfromance on some tasks (e.g. SQuAD), but weakly with other tasks (e.g. QNLI or MRPC). For all of the tasks³ where the correlation with model size $r^2 < 0.3$, we obtain a correlation with \mathcal{X}_{γ^*} of $r^2 > 0.75$, reinforcing the claim that concept expertise \mathcal{X}_{γ^*} is a good measure of generalization.

Models used	Task	(S)	(T)	$\mathcal{X}_{\gamma^{\star}}$
	GLUE Score	0.361	0.871	0.892
	CoLA	0.572	0.821	0.874
	SST-2	0.554	0.849	0.864
	MRPC (acc)	0.163	0.714	0.753
DEDT D/I	MRPC (F1)	0.162	0.916	0.855
BERT-B/L	STS-B (p)	0.000	0.490	0.401
Distilbert	STS-B (s)	0.115	0.903	0.840
RoBERTa-L	QQP (acc)	0.340	0.936	0.944
XLM	QQP (F1)	0.397	0.834	0.859
	MNLI-m	0.603	0.833	0.771
	MNLI-mm	0.452	0.906	0.944
	QNLI	0.286	0.857	0.923
	RTE	0.332	0.861	0.873
	WNLI	0.314	0.751	0.619
	AX	0.426	0.914	0.956
BERT-B/L				
DistilBERT	SQuAD 1.1 (F1)	0.899	0.840	0.850
RoBERTa-L	SQuAD 2.0 (F1)	0.961	0.752	0.937
	Average	0.408	0.826	0.833

Table 2: Squared Pearson's coefficient (r^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 \mathcal{X}_{γ^*} (Eq. (3)). Only those models reporting results on each dataset are used (first column). On average, the correlation using \mathcal{X}_{γ^*} (0.833) is better than the average correlation among all tasks (0.826), the latter requires 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 $\tau_c = \text{percentile}_{99}(AP_c^m)$ per concept, then we define $s_c = \{1 \text{ if } AP_c^m > \tau_c \text{ else } 0\} \in \mathbb{Z}_2^M$ as our binary concept representation. Note that s_c has elements with value 1 for the top 1% units classifying the concept. Let the overlap between concepts q and v be

$$\Omega(q, v) = \frac{\|\mathbf{s}_q \cap \mathbf{s}_v\|_1}{\|\mathbf{s}_q \cup \mathbf{s}_v\|_1} \in [0, 1], \tag{4}$$

representing the number of top units that classify both concepts with high AP_c^m .

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 $\Omega(q, v)$ (defined in Eq. (4))

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.

Query definition	Concept	$\Omega({\color{red}q},v)$
	chair%1:06:00 (query)	1.000
A seat for one	table%1:06:01	0.458
person, with a support for the back.	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
	chair%1:04:00 (query)	1.000
The position	chair%1:04:00 VS. chair%1:06:00	0.575
*	fellow%1:18:02	0.371
of professor.	director%1:18:03	0.297
	administration%1:04:00	0.243
	member%1:18:00	0.241

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.

with a query concept q. The query concepts considered are represented by the same word (chair) but with different WordNet sense (first row of Table 3). Observe how the top-5 concepts are coherent with the definition of the query. The fact that the *homograph* concept that disambiguates the query appears with high overlap is also interesting. Concept co-learning can be used for explainability: given a concept with unknown definition (e.g. failure cases in a dialogue system), the overlapping concepts can help explain it. See Appendix C for more results including t-SNE projections [34] of s_c .

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 [5] 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 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

K forced	Once upon a time + 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.\n 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.\n But this wonder of the air has no such wings.\n Taking down
200 (0.048%)	of year, birds chase each and watching. flot racing form, 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

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%1:27:00 and lead%1:07:02, showing the model's ability to capture the meaning of the concept.

exploration in the generative field, although extremely interesting, is out of scope for this work.

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_c^m 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

 $\sim 2.5 M$ 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 $\mathrm{AP}_c^m \ \forall m,c$ requires, in the GPT2-L case, 414720×1641 floats $\approx 2.5\mathrm{GB}$ 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 experts 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

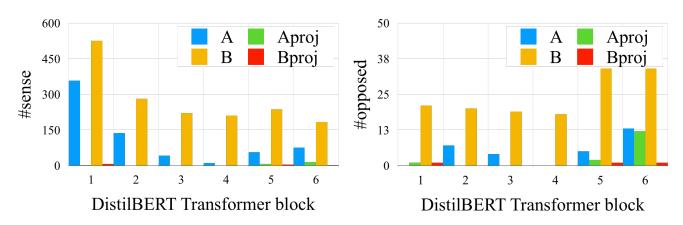


Figure 5: Concept distribution per layer at $\gamma = 0.95$ for model DistilBERT.

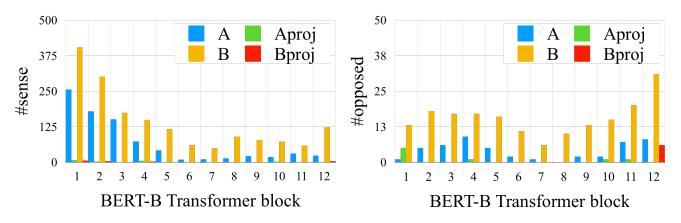


Figure 6: Concept distribution per layer at $\gamma = 0.95$ for model BERT-B.

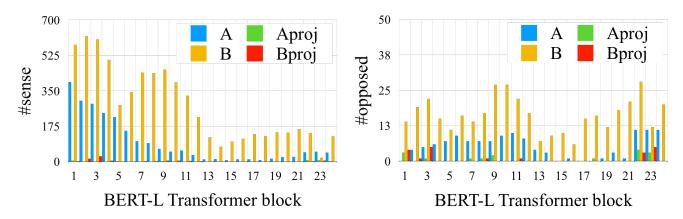


Figure 7: Concept distribution per layer at $\gamma = 0.95$ for model BERT-L.

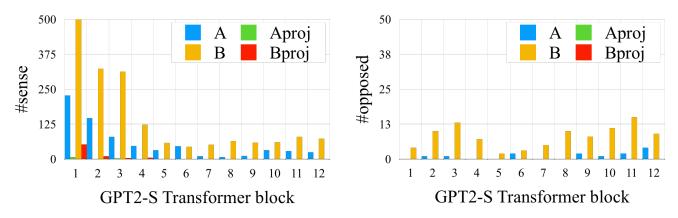


Figure 8: Concept distribution per layer at $\gamma = 0.95$ for model GPT2-S.

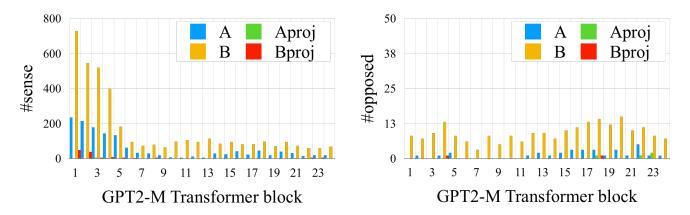


Figure 9: Concept distribution per layer at $\gamma = 0.95$ for model GPT2-M.

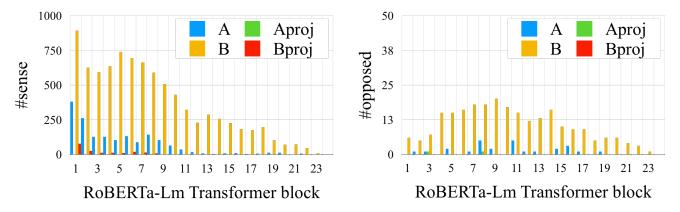


Figure 10: Concept distribution per layer at $\gamma=0.95$ for model RoBERTa-Lm.

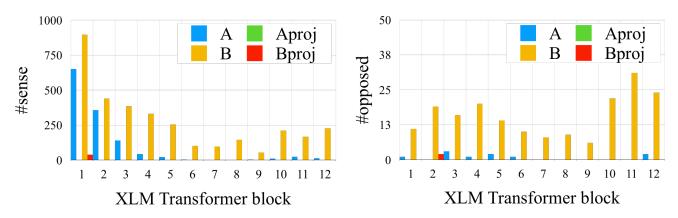


Figure 11: Concept distribution per layer at $\gamma=0.95$ for model XLM.

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%1:06:01	sense	0.458	a piece of furniture having a smooth flat top that is usually supported by one or more vertical legs
bed%1:06:00	sense	0.361	a piece of furniture that provides a place to sleep
cup%1:06:00	sense	0.341	a small open container usually used for drinking; usually has a handle
table%1:06:01 VS. table%1:14:00	homograph	0.336	a piece of furniture having a smooth flat top that is usually supported by one or more vertical legs VS. a set of data arranged in rows and columns
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 VS. chair%1:06:00	homograph	0.575	the position of professor VS. a seat for one person, with a support for the back
fellow%1:18:02	sense	0.371	a friend who is frequently in the company of another
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 (espe- cially 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%1:28:00	sense	1.000	a time interval during which there is a temporary cessation of something
suspension%1:28:00 VS. suspension%1:27:00	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	return to an original state
season%1:28:02	sense	0.396	a period of the year marked by special events or activities in some field
prospect%1:26:00	sense	0.387	the possibility of future success
attempt%1:04:00	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%1:27:00	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%1:27:00	sense	0.432	the tangible substance that goes into the makeup of a physical object
powder%1:27:00	sense	0.415	a solid substance in the form of tiny loose particles; a solid that has been pulver
10/1 27 00		0.412	ized
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 trans-
subscriber%1:18:01		0.423	mitted over distances and then converts received signals back into sounds someone who contracts to receive and pay for a service or a certain number of
Subscriber%1:18:01	sense	0.423	issues of a publication
talk%1:10:00	sense	0.344	an exchange of ideas via conversation
need%1:17:00 VS. need%1:26:00	homograph	0.328	anything that is necessary but lacking VS. a condition requiring relief
user%1:18:00	sense	0.321	a person who makes use of a thing; someone who uses or employs something
message%1:10:01	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 VS. phone%1:06:00	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 con- verts 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 VS. american%1:18:00	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
	501.50	0.27.	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.

Concept	Type	Overlap	WordNet 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
market%1:14:00	sense	1.000	the customers for a particular product or service
market%1:04:00	sense	0.353	the world of commercial activity where goods and services are bought and sold
industry%1:14:00	sense	0.221	the people or companies engaged in a particular kind of commercial enter- prise
banking%1:04:00	sense	0.211	transacting business with a bank; depositing or withdrawing funds or requesting a loan etc.
market%1:14:00 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

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 $AP_c^{\star}=0.523$.

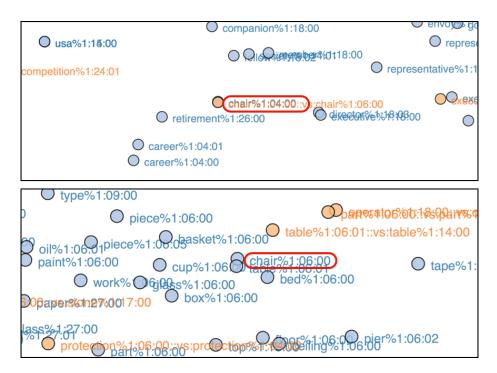


Figure 12: t-SNE projection of the concept representations s_c proposed in Sec. 5. Zoom-in on concepts chair%1:04:00 and chair%1:06:00, whose meaning can easily be explained by their neighbors. The t-SNE projection is an alternative view of the nearest neighbor results shown in Table 6. In orange *homograph*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

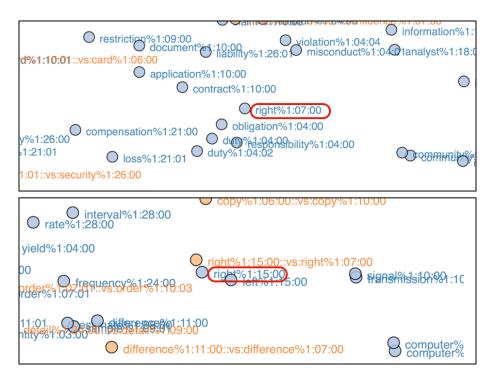


Figure 13: t-SNE projection of the concept representations s_c proposed in Sec. 5. Zoom-in on conceptsright%1:07:00 and right%1:15:00, whose meaning can easily be explained by their neighbors. In orange *homograph* concepts.

D. Conditioned generation extended results

K forced	WordNet concept	AP_c^\star	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 beautiful 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. Yet 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 8: Extended results on successful conditioned generation. All the concepts shown have an $AP_c^{\star} \geq \gamma^{\star}$. We borrow the context from the OpenAI GPT2 work [27]

K forced	WordNet concept	AP_c^\star	Context + Generated (conditioned to concept)
40	work%1:06:00	0.8508	Once upon a time, in an ancient palace at the heart of history, a was on. Magic, symbolism, decadence and tragedy. Everything had come up, balancing with the architect's.\n\nA madman's museum. A thing of daub. Now, it's hide and clay and mud and dirt
70	work%1:06:00	0.8508	Once upon a time-spotted bench). Now I met my tools,, work, work, < endoftext >Raw Products Kretzer Top Tube Process\n\nPROTECT SHOP:\n\nDay 1: Screening on the work bench.\n\n\n1. Beaksiewerk procedure - drill build
100	work%1:06:00	0.8508	Once upon a time of WARD will i means to out out any.\n:,. So! Work- WORK WORK WORK WORK WORK WORK\n WORK\n WORK\n work work work\n work\n work work work work work work work work
200	work%1:06:00	0.8508	Once upon a time of that done by uses of such done object\n\n of.\n 28, 37\n WORK WORK WORK work article delivery (bench work\n call really work\n out\n work work work 40 work product if 5 40 work work 50\n work work 35 means 34 twenty block 29 individual

Table 9: Extended results on unsuccessful conditioned generation. The concept has $AP_c^{\star} \ll \gamma^{\star}$, and we observe how the model struggles to produce legible sentences.

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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_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 $AP_c^* = 0.9885$, 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 $AP_c^* = 0.8779$.

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

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_c^\star	sense concept	AP_c^{\star}	sense concept	AP _c	sense concept	AP_c^{\star}	sense concept
1.0000		0.9992	sin%1:07:00	0.9983	cab%1:06:02	0.9976	memory%1:09:02
1.0000 1.0000	console%1:06:03 connecticut%1:17:00	0.9991 0.9991	sum%1:09:01 companion%1:18:00	0.9983	text%1:10:03 crystal%1:27:00	0.9976	exception%1:09:00 doctor%1:18:00
1.0000	thanks%1:10:00	0.9990	worker%1:18:00	0.9982	backing%1:04:00	0.9975	plot%1:15:00
1.0000		0.9990	mouth%1:08:01 dollar%1:23:00	0.9982	establishment%1:04:00 eruption%1:11:00	0.9975	estimate%1:09:00 town%1:15:00
0.9999	elevator%1:06:00	0.9990	journalist%1:18:00	0.9982	council%1:14:02	0.9975	shelter%1:06:00
0.9999	reply%1:10:01 smell%1:09:02	0.9990	illusion%1:09:01 sign%1:10:05	0.9982	integrity%1:26:00 figure%1:10:00	0.9975	profession%1:14:00 release%1:06:00
0.9999		0.9989	contract%1:10:00	0.9982	score%1:09:00	0.9975	fee%1:21:00
0.9999	hangover%1:26:00	0.9989	concentration%1:07:02	0.9982	barrier%1:06:00 understanding%1:09:01	0.9975 0.9975	message%1:10:00
0.9999	skin%1:08:00 smoke%1:19:00	0.9989	behalf%1:04:00 frequency%1:28:00	0.9982	barrel%1:06:01	0.9975	defect%1:26:01 recommendation%1:10:00
0.9999	•	0.9989	fit%1:26:01	0.9981	competition%1:24:01	0.9975	migration%1:04:00
0.9998		0.9988 0.9988	plane%1:06:01 category%1:14:00	0.9981	retirement%1:26:00 prospect%1:26:00	0.9974	fishing%1:04:00 presence%1:26:00
0.9998	exercise%1:04:00	0.9988	drink%1:13:04	0.9981	3d%1:10:00	0.9974	suit%1:06:00
0.9998		0.9988	injection%1:27:00 stranger%1:18:00	0.9981	attraction%1:19:00 envoy%1:18:00	0.9974	file%1:10:00 regulator%1:06:00
0.9997	confusion%1:26:01	0.9988	liquor%1:13:00	0.9981	card%1:10:01	0.9974	evening%1:28:00
0.9997 0.9997	mess%1:26:00 invasion%1:04:00	0.9988 0.9988	office%1:06:00 personality%1:07:00	0.9981	pocket%1:06:00 suspension%1:27:00	0.9974	practice%1:04:00 screen%1:06:06
0.9997	subscriber%1:18:02	0.9988	chamber%1:06:00	0.9980	sort%1:09:00	0.9974	hall%1:06:05
0.9997		0.9987	flood%1:19:00	0.9980	liquor%1:27:00	0.9973	contribution%1:04:02
0.9997 0.9997		0.9987 0.9987	emission%1:04:00 spring%1:28:00	0.9980	vote%1:04:00 bonus%1:09:00	0.9973	friend%1:18:03 average%1:24:00
0.9997	gold%1:21:00	0.9987	addiction%1:26:00	0.9980	gathering%1:14:00	0.9973	pair%1:14:01
0.9996 0.9996		0.9987 0.9987	substance%1:03:00 brazil%1:15:00	0.9980	loan%1:21:00 tenant%1:18:00	0.9973	counterpart%1:09:00 mg%1:23:00
0.9996		0.9987	backing%1:06:00	0.9979	attitude%1:09:00	0.9973	vicar%1:18:02
0.9995		0.9987	bourbon%1:18:01	0.9979	height%1:07:00	0.9972	cloud%1:19:01
0.9995 0.9995		0.9986 0.9986	move%1:04:00 sound%1:07:00	0.9979	identity%1:09:00 copy%1:10:00	0.9972 0.9972	jury%1:14:00 deal%1:04:02
0.9995	baby%1:18:00	0.9986	equity%1:21:01	0.9978	negotiation%1:04:00	0.9972	tissue%1:08:00
0.9994 0.9994	expression%1:07:00 participant%1:18:00	0.9985 0.9985	phone%1:06:00 maintenance%1:04:00	0.9978	ritual%1:04:00 couple%1:14:00	0.9972	arm%1:08:00 sense%1:09:05
0.9994		0.9985	charge%1:04:01	0.9978	revolution%1:04:00	0.9972	contrast%1:24:00
0.9994 0.9994	budget%1:21:02 misconduct%1:04:01	0.9985 0.9985	farmer%1:18:00 tower%1:06:00	0.9978	circle%1:25:00 corner%1:15:02	0.9971 0.9971	transmission%1:10:00 light%1:19:00
0.9994		0.9984	frustration%1:12:00	0.9978	operator%1:24:00	0.9971	scene%1:15:00
0.9994		0.9984	depth%1:07:00	0.9978	negotiation%1:10:00	0.9971	behalf%1:07:00
0.9993		0.9984	prayer%1:04:00 surprise%1:12:00	0.9978	brain%1:08:00 israel%1:15:00	0.9971	storm%1:19:00 cash%1:21:00
0.9993	message%1:10:01	0.9984	nightmare%1:26:00	0.9977	reaction%1:22:00	0.9971	portfolio%1:14:00
0.9993	colon%1:08:00 pursuit%1:04:00	0.9984	colleague%1:18:00 drinking%1:04:01	0.9977	overhaul%1:04:00 mind%1:09:01	0.9971	attention%1:09:00 mandate%1:10:00
0.9993	speculation%1:10:03	0.9984	traffic%1:14:00	0.9976	ceiling%1:06:00	0.9971	sentence%1:10:00
0.9992 0.9992		0.9983	wheel%1:06:00 cup%1:06:00	0.9976	code%1:10:01 identity%1:07:00	0.9971	trainer%1:18:00 discussion%1:10:02
0.9992		0.9983	winner%1:18:00	0.9976	representative%1:18:02	0.9970	round%1:06:01
0.9970 0.9970	paper%1:27:00 volume%1:23:00	0.9963 0.9963	check%1:21:00 sin%1:04:00	0.9956 0.9956	sport%1:04:00 satisfaction%1:12:00	0.9950 0.9950	subject%1:10:00 retirement%1:04:00
0.9970		0.9963	table%1:14:00	0.9956	chair%1:04:00	0.9950	population%1:14:00
0.9970		0.9962	subscriber%1:18:01	0.9955	tape%1:06:00	0.9950	cloud%1:17:00
0.9969		0.9962 0.9962	powder%1:27:00 output%1:04:00	0.9955	earthquake%1:11:00 duty%1:04:00	0.9950	pleasure%1:12:00 representative%1:18:00
0.9969	major%1:18:00	0.9962	scorer%1:18:00	0.9955	master%1:18:00	0.9949	personnel%1:14:00
0.9969	pattern%1:09:00 visit%1:04:02	0.9962	card%1:06:00 material%1:27:00	0.9955	variable%1:09:00 deposit%1:19:00	0.9949	survey%1:04:02 array%1:14:00
0.9969	test%1:09:02	0.9962	radiation%1:19:00	0.9954	floor%1:06:00	0.9949	sport%1:04:01
0.9969 0.9968		0.9962 0.9962	division%1:14:00 growth%1:22:00	0.9954	intensity%1:07:03 comment%1:10:00	0.9949	craft%1:04:00 plot%1:09:00
0.9968	staff%1:14:01	0.9961	spot%1:15:01	0.9954	triumph%1:11:00	0.9949	draft%1:21:00
0.9968	pound%1:23:01	0.9961	mood%1:12:00	0.9954	rest%1:24:00	0.9949	fate%1:11:00
0.9968 0.9968	isolation%1:26:00 effort%1:04:00	0.9961 0.9960	look%1:07:01 unit%1:23:00	0.9954	drinking%1:04:00 rhythm%1:07:01	0.9949 0.9948	reason%1:16:00 diversity%1:07:02
0.9968	wish%1:12:00	0.9960	delivery%1:04:04	0.9954	liability%1:26:01	0.9948	balloon%1:06:00
0.9968		0.9960 0.9960	pilot%1:18:00 class%1:14:00	0.9953	aspect%1:09:00 ton%1:23:02	0.9948	address%1:10:04 nut%1:20:00
0.9967	nightmare%1:09:00	0.9960	minute%1:28:00	0.9953	doctor%1:18:02	0.9947	mouse%1:05:00
0.9967 0.9967		0.9960 0.9960	vein%1:08:00 shop%1:06:00	0.9953	variety%1:14:01 trade%1:04:05	0.9947 0.9947	mode%1:07:00 ground%1:17:00
0.9967	couple%1:14:01	0.9960	executive%1:18:00	0.9953	rule%1:09:00	0.9947	complaint%1:26:00
0.9967		0.9959	welfare%1:04:00	0.9953	copy%1:06:00	0.9947	insight%1:09:02
0.9967 0.9967	neighbor%1:18:00 sanction%1:10:00	0.9959 0.9959	mystery%1:09:00 contractor%1:18:00	0.9953 0.9953	sound%1:09:00 contact%1:04:02	0.9947 0.9946	peak%1:23:00 replacement%1:04:00
0.9966	note%1:10:00	0.9959	obligation%1:04:00	0.9953	bill%1:10:04	0.9946	adaptation%1:10:00
0.9966 0.9966		0.9959	claim%1:10:00 dinner%1:14:00	0.9953	option%1:21:00 trial%1:04:00	0.9946 0.9946	republican%1:18:01 bed%1:06:00
0.9966	stone%1:17:00	0.9959	violation%1:04:00	0.9952	envoy%1:18:01	0.9946	powder%1:27:01
0.9966 0.9966	bond%1:21:02 appeal%1:07:00	0.9959	employment%1:26:00 pleasure%1:09:00	0.9952	week%1:28:00 cleveland%1:15:00	0.9946	honor%1:10:00 news%1:10:00
0.9965	horn%1:06:06	0.9958	edition%1:10:02	0.9952	flower%1:20:00	0.9946	help%1:04:00
0.9965 0.9965		0.9958 0.9958	gender%1:10:00 duck%1:05:00	0.9952 0.9952	formation%1:14:00	0.9945 0.9944	status%1:26:00 discovery%1:04:00
0.9963		0.9958	duck%1:05:00 bronze%1:27:00	0.9952	category%1:09:02 bell%1:06:00	0.9944	discovery%1:04:00 tie%1:06:01
0.9964	source%1:15:00	0.9957	triumph%1:12:00	0.9951	commerce%1:14:00	0.9944	commission%1:14:00
0.9964 0.9964	ministry%1:14:01 grievance%1:10:01	0.9957 0.9957	wealth%1:26:00 usa%1:15:00	0.9951	church%1:14:00 suspension%1:28:00	0.9944	pressure%1:19:00 path%1:04:00
0.9964	flexibility%1:07:02	0.9957	justice%1:07:00	0.9951	chart%1:10:00	0.9944	event%1:03:00
0.9964 0.9964		0.9957 0.9957	woman%1:18:00 market%1:14:00	0.9951	sunday%1:28:00 instruction%1:10:04	0.9943 0.9943	job%1:04:00 swing%1:26:01
0.9964	text%1:10:00	0.9957	plane%1:25:00	0.9951	partner%1:18:01	0.9943	intention%1:09:00
0.9963		0.9956	striker%1:18:02	0.9951	front%1:15:00	0.9943	dispute%1:10:00
0.9963			timac@-1.29.01				
0.9963	evidence%1:09:00	0.9956 0.9956	times%1:28:01 wind%1:19:00	0.9951	budget%1:21:03 moon%1:17:01	0.9943 0.9943	cost%1:21:00 weight%1:07:00
0.9963	evidence%1:09:00 fear%1:12:00 violation%1:04:04	0.9956 0.9956 0.9956	wind%1:19:00 representation%1:09:00	0.9951 0.9951	moon%1:17:01 shadow%1:26:01	0.9943 0.9943	weight%1:07:00 repression%1:26:00
	evidence%1:09:00 fear%1:12:00 violation%1:04:04 favor%1:04:00	0.9956 0.9956	wind%1:19:00	0.9951	moon%1:17:01	0.9943	weight%1:07:00

AP_c^{\star}	sense concept	AP _c	sense concept	AP _c	sense concept	AP _c	sense concept
0.9942	brand%1:10:00	0.9934	pier%1:06:00	0.9926	question%1:10:00	0.9917	interval%1:28:00
0.9942	energy%1:19:00	0.9934	power%1:07:00	0.9926	current%1:19:01	0.9917	focus%1:09:00
0.9941	opponent%1:18:02	0.9934	money%1:21:00	0.9926	china%1:15:00	0.9916	judge%1:18:00
0.9941	sale%1:04:00 root%1:20:00	0.9934	delivery%1:11:00 commerce%1:04:00	0.9925	talk%1:10:00 accumulation%1:22:00	0.9916 0.9916	outlet%1:06:01 stage%1:28:00
0.9941	scale%1:24:03	0.9934	battery%1:14:02	0.9925	trend%1:15:02	0.9916	piece%1:06:00
0.9941	security%1:26:00	0.9934	left%1:15:00	0.9925	leader%1:18:00	0.9916	routine%1:10:01
0.9941	bird%1:13:00 conference%1:14:00	0.9933	entrance%1:06:00 filing%1:10:00	0.9924	fight%1:04:01 head%1:08:00	0.9915 0.9915	relation%1:03:00 yield%1:04:00
0.9940	capital%1:21:01	0.9933	lead%1:07:02	0.9924	progress%1:04:01	0.9915	movement%1:04:00
0.9940	fall%1:28:00	0.9933	communication%1:10:01	0.9924	environment%1:26:00	0.9914	intervention%1:04:00
0.9940	league%1:14:00	0.9932	dinner%1:13:00	0.9924	information%1:10:00	0.9914	conservative%1:18:01
0.9940 0.9940	russia%1:15:01 hand%1:08:00	0.9932	friend%1:18:00 impact%1:11:00	0.9924 0.9923	danger%1:26:00 hall%1:06:03	0.9914 0.9913	distinction%1:09:00 range%1:07:00
0.9940	panama%1:15:00	0.9932	step%1:04:02	0.9923	radio%1:10:00	0.9913	round%1:28:01
0.9940	shock%1:04:01	0.9932	article%1:10:00	0.9923	master%1:18:04	0.9913	bonus%1:21:00
0.9939	football%1:04:00 nickname%1:10:01	0.9932	obstacle%1:09:00 shelter%1:06:01	0.9923	advent%1:04:00 driver%1:18:00	0.9913	blood%1:08:00 emphasis%1:26:00
0.9939	voice%1:07:00	0.9932	race%1:11:01	0.9923	background%1:07:00	0.9913	earth%1:17:00
0.9939	eye%1:08:00	0.9932	craft%1:06:00	0.9922	news%1:10:01	0.9913	flow%1:11:00
0.9939	youth%1:18:00 bell%1:06:02	0.9931	personality%1:18:00 pet%1:05:00	0.9922	community%1:14:00	0.9912 0.9912	right%1:15:00 mistaka%1:04:00
0.9939	departure%1:04:00	0.9931	attendance%1:04:00	0.9922	thought%1:09:01 dance%1:10:00	0.9912	mistake%1:04:00 actor%1:18:00
0.9939	winner%1:18:01	0.9930	combination%1:14:00	0.9922	draft%1:19:00	0.9911	trainer%1:06:00
0.9938	sideline%1:15:00	0.9930	account%1:10:00	0.9922	water%1:27:00	0.9911	past%1:28:00
0.9938	equity%1:21:00 machine%1:06:00	0.9930	investigation%1:09:00 door%1:06:00	0.9921	labor%1:14:00 experiment%1:04:00	0.9911	chance%1:19:00 shock%1:12:01
0.9938	fishing%1:04:01	0.9930	intervention%1:10:00	0.9921	reduction%1:04:00	0.9910	document%1:10:00
0.9938	cancer%1:26:00	0.9930	morning%1:28:00	0.9921	color%1:07:00	0.9910	truck%1:06:01
0.9937	wave%1:11:01	0.9930	generalization%1:09:01	0.9921	regulation%1:10:00	0.9910	election%1:04:01
0.9937 0.9937	cat%1:05:00 killer%1:18:00	0.9930	strategy%1:09:00 border%1:15:00	0.9921	face%1:08:00 agent%1:18:02	0.9910 0.9910	favor%1:07:00 sentence%1:04:00
0.9937	spine%1:08:00	0.9929	violence%1:04:01	0.9920	margin%1:25:00	0.9909	crossing%1:17:00
0.9937	factor%1:11:00	0.9929	name%1:10:00	0.9920	market%1:04:00	0.9909	suit%1:04:00
0.9936	boost%1:04:00 metal%1:27:00	0.9929	mouth%1:08:00 bond%1:19:00	0.9920	dose%1:06:00 computer%1:06:00	0.9909	infrastructure%1:06:01 length%1:07:00
0.9936	side%1:15:02	0.9928	diet%1:13:00	0.9920	report%1:10:03	0.9909	action%1:04:02
0.9936	debate%1:10:01	0.9928	memory%1:09:01	0.9919	client%1:18:00	0.9908	trip%1:26:00
0.9936	today%1:28:00	0.9928	angle%1:25:00	0.9919	proposal%1:10:00	0.9908	plus%1:07:00
0.9936	expenditure%1:21:00 virtue%1:07:01	0.9928	responsibility%1:04:00 solution%1:27:00	0.9918	threat%1:26:00 football%1:06:00	0.9908	season%1:28:02 usa%1:14:00
0.9935	weight%1:06:01	0.9927	compensation%1:21:00	0.9918	addition%1:06:00	0.9908	angle%1:09:00
0.9935	chair%1:06:00	0.9927	risk%1:26:00	0.9918	flower%1:20:02	0.9907	technology%1:04:00
0.9935	medicine%1:09:00 assumption%1:10:00	0.9927	street%1:06:00 return%1:10:01	0.9918	camera%1:06:00 language%1:10:00	0.9907 0.9907	show%1:04:00 trip%1:04:00
0.9935	dream%1:09:01	0.9927	analyst%1:18:00	0.9917	structure%1:06:00	0.9907	capability%1:07:00
0.9935	foot%1:08:01	0.9927	russia%1:15:00	0.9917	defense%1:04:03	0.9907	advantage%1:07:00
0.9935	brazil%1:13:00	0.9927	hunter%1:18:00 cut%1:10:00	0.9917	examination%1:04:00	0.9907 0.9907	application%1:04:02
0.9933	nobility%1:14:00 disco%1:10:00	0.9927	tone%1:10:01	0.9917	poster%1:18:00 beat%1:15:00	0.9907	kid%1:18:00 planet%1:17:00
0.9906	stake%1:21:02	0.9893	maintenance%1:21:00	0.9882	dispute%1:04:00	0.9868	economy%1:14:00
0.9906	sample%1:09:01	0.9893	stance%1:07:00	0.9881	reference%1:10:02	0.9868	user%1:18:00
0.9906 0.9905	interference%1:10:00 glass%1:27:00	0.9892	jury%1:14:01 window%1:06:00	0.9881	leadership%1:04:00 record%1:10:03	0.9868 0.9868	goal%1:09:00 colleague%1:18:01
0.9905	basket%1:06:00	0.9892	flow%1:28:00	0.9881	english%1:10:00	0.9868	duck%1:23:00
0.9904	top%1:15:01	0.9892	experience%1:09:01	0.9880	course%1:04:01	0.9867	sign%1:10:00
0.9904	committee%1:14:00	0.9892	wheel%1:06:05	0.9880	patient%1:18:00	0.9867	limit%1:07:00
0.9904	commission%1:21:00 director%1:18:00	0.9891	act%1:10:01 benefit%1:21:00	0.9880	temperature%1:07:00 relative%1:18:00	0.9867 0.9867	agent%1:17:00 opinion%1:09:00
0.9904	guest%1:18:00	0.9891	detail%1:09:00	0.9880	mind%1:09:00	0.9867	thanks%1:04:00
0.9904	paint%1:06:00	0.9891	council%1:14:01	0.9879	match%1:06:00	0.9866	teaching%1:04:00
0.9904	function%1:24:00 situation%1:26:00	0.9891	compensation%1:22:00 administration%1:04:00	0.9879 0.9879	room%1:06:00 birth%1:28:00	0.9866 0.9866	distinction%1:26:00 increase%1:23:00
0.9903	difference%1:07:00	0.9891	heel%1:06:00	0.9878	environment%1:15:00	0.9866	interest%1:09:00
0.9903	appearance%1:11:00	0.9890	isolation%1:12:00	0.9878	operator%1:18:00	0.9866	court%1:14:00
0.9903	club%1:14:01 banking%1:04:01	0.9890	box%1:06:00	0.9878	space%1:25:00	0.9866	giant%1:05:00 client%1:18:01
0.9903	guy%1:18:00	0.9890	game%1:04:00 training%1:04:00	0.9877	parish%1:15:00 floor%1:06:01	0.9866	client%1:18:01 barrier%1:09:00
0.9902	stranger%1:18:01	0.9889	purpose%1:09:00	0.9877	log%1:10:01	0.9865	sunday%1:18:00
0.9901	field%1:15:00	0.9889	senate%1:14:00	0.9876	washington%1:15:01	0.9865	region%1:15:00
0.9901 0.9901	gas%1:26:00 face%1:07:03	0.9889	crystal%1:06:02 address%1:15:00	0.9876 0.9876	right%1:07:00 meeting%1:14:00	0.9865 0.9864	pet%1:18:00 league%1:14:01
0.9901	limit%1:28:00	0.9889	camera%1:06:01	0.9876	signal%1:10:00	0.9864	attempt%1:04:00
0.9900	polyp%1:26:00	0.9888	official%1:18:01	0.9876	index%1:24:00	0.9864	grade%1:14:00
0.9900 0.9899	return%1:04:01 challenge%1:10:00	0.9888	baby%1:18:01 element%1:09:00	0.9876 0.9875	basis%1:24:00 attendance%1:28:00	0.9864 0.9863	challenge%1:26:00 program%1:09:00
0.9899	guy%1:06:01	0.9887	hell%1:11:00	0.9875	minister%1:18:00	0.9863	governor%1:18:00
0.9899	care%1:04:01	0.9887	duty%1:04:02	0.9874	variation%1:11:01	0.9863	rank%1:14:00
0.9899	seat%1:15:01	0.9887	signal%1:16:00	0.9874	conservative%1:18:00	0.9862	example%1:09:00
0.9899 0.9899	journalist%1:18:01 bid%1:04:00	0.9887	insight%1:12:00 performance%1:10:00	0.9873	canon%1:10:00 candidate%1:18:01	0.9862 0.9862	session%1:28:00 arrival%1:04:01
0.9898	rank%1:26:00	0.9887	london%1:15:00	0.9873	project%1:04:00	0.9861	body%1:08:00
0.9897	family%1:14:02	0.9886	space%1:03:00	0.9873	loss%1:21:01	0.9861	treatment%1:04:01
0.9897 0.9897	acceptance%1:09:00 protection%1:04:00	0.9886	involvement%1:24:00 rate%1:28:00	0.9872 0.9872	story%1:10:03 instability%1:07:01	0.9861	plan%1:09:00 decision%1:04:00
0.9897	killer%1:26:00	0.9886	success%1:11:00	0.9872	home%1:06:00	0.9859	wish%1:10:00
0.9897	union%1:14:01	0.9885	times%1:04:00	0.9872	youth%1:14:00	0.9859	art%1:06:00
0.9896	personnel%1:14:01	0.9885	one%1:23:00	0.9871	lead%1:27:00	0.9859	france%1:15:00
0.9896 0.9896	advance%1:11:00 bluff%1:17:00	0.9885	cycle%1:14:00 education%1:04:00	0.9871	term%1:10:00 investment%1:04:00	0.9859 0.9858	move%1:04:01 chamber%1:08:00
0.9895	bit%1:23:01	0.9885	posture%1:07:00	0.9870	border%1:25:00	0.9858	deal%1:10:00
0.9895	code%1:10:00	0.9885	tea%1:13:00	0.9870	resident%1:18:00	0.9858	democracy%1:14:00
0.9895 0.9895	viewpoint%1:09:00	0.9885	birth%1:11:00 car%1:06:00	0.9870 0.9870	israel%1:15:01 inclusion%1:26:00	0.9858 0.9858	amount%1:21:00 heart%1:08:00
0.9895	defense%1:04:00 carnival%1:04:00	0.9884	advance%1:11:01	0.9870	solution%1:26:00	0.9858	liability%1:26:00
0.9894	kingdom%1:26:00	0.9883	heel%1:08:00	0.9869	foundation%1:24:00	0.9857	par%1:23:00
0.9894	selection%1:04:00	0.9883	bronze%1:06:00	0.9869	cause%1:11:00	0.9857	announcement%1:10:01
0.9893 0.9893	search%1:04:00 noise%1:11:00	0.9883	future%1:28:00 administration%1:14:00	0.9869 0.9869	pupil%1:18:00 drink%1:04:00	0.9857 0.9856	female%1:05:00 shop%1:06:01
0.9893	obstacle%1:06:00	0.9882	night%1:28:00	0.9869	industry%1:14:00	0.9856	companion%1:18:02

AP_c^{\star}	sense concept	AP*	sense concept	AP_c^{\star}	sense concept	AP_c^{\star}	sense concept
0.9856	cash%1:21:02	0.9835	obligation%1:26:00	0.9815	exposure%1:04:06	0.9787	interval%1:09:00
0.9856 0.9856	fellow%1:18:02	0.9835	partner%1:18:00	0.9814 0.9814	machine%1:18:00	0.9786 0.9785	help%1:18:00
0.9855	extent%1:26:00 blood%1:07:00	0.9834 0.9834	input%1:10:00 force%1:19:00	0.9813	minute%1:28:01 visit%1:14:00	0.9785	influence%1:07:00 whole%1:09:00
0.9855	decision%1:09:00	0.9833	cell%1:06:03	0.9813	treatment%1:04:00	0.9785	influence%1:04:00
0.9854 0.9853	balloon%1:06:01 surgery%1:06:01	0.9832	book%1:10:00 assessment%1:09:00	0.9810 0.9810	candidate%1:18:00 hand%1:18:00	0.9785 0.9784	height%1:26:00 worker%1:18:01
0.9853	start%1:11:00	0.9832	perimeter%1:25:00	0.9809	prayer%1:10:02	0.9782	wind%1:19:01
0.9853	senate%1:14:01	0.9831	edition%1:14:00	0.9808	major%1:18:02	0.9782	series%1:14:00
0.9852 0.9852	nation%1:14:00 list%1:10:00	0.9831	band%1:14:00 authority%1:07:00	0.9808 0.9808	bank%1:17:01 circus%1:14:00	0.9782 0.9781	low%1:26:00 restriction%1:09:00
0.9852	programme%1:10:00	0.9830	damage%1:11:00	0.9806	pocket%1:25:00	0.9781	gas%1:27:00
0.9851	congress%1:14:01	0.9829	letter%1:10:00	0.9805	minister%1:18:02	0.9780	gender%1:07:00
0.9850 0.9850	age%1:07:00 heart%1:09:00	0.9828 0.9827	role%1:04:00 hour%1:28:00	0.9805 0.9805	school%1:14:00 force%1:07:01	0.9780 0.9780	application%1:10:00 idea%1:09:01
0.9849	change%1:11:00	0.9827	broadcaster%1:06:00	0.9805	sense%1:10:00	0.9780	back%1:08:00
0.9849	tenant%1:18:02	0.9827	parish%1:14:00	0.9804	alarm%1:12:00	0.9778	kitty%1:21:01
0.9848 0.9848	march%1:28:00 concern%1:09:00	0.9827	authority%1:18:01 research%1:04:00	0.9804 0.9803	crisis%1:11:00 trade%1:04:00	0.9777 0.9777	loss%1:22:00 investment%1:21:00
0.9847	tablet%1:06:02	0.9826	comment%1:10:01	0.9803	result%1:19:00	0.9777	child%1:18:00
0.9847	american%1:18:00	0.9826	factor%1:09:00	0.9803	woman%1:18:01	0.9777	number%1:07:00
0.9847 0.9846	intention%1:09:01 philosophy%1:09:01	0.9826 0.9826	matter%1:09:01 way%1:07:01	0.9802 0.9801	dream%1:09:02 house%1:06:00	0.9775 0.9774	bottom%1:15:00 decade%1:28:00
0.9846	development%1:04:01	0.9825	involvement%1:04:00	0.9801	whole%1:03:00	0.9774	phone%1:10:00
0.9845	duration%1:28:02	0.9825	step%1:23:00	0.9801	goal%1:15:00	0.9773	medicine%1:06:00
0.9845 0.9845	receptor%1:08:00 proportion%1:24:00	0.9825 0.9824	institution%1:14:00 journal%1:10:01	0.9801 0.9800	principal%1:18:00 cab%1:06:01	0.9773 0.9770	season%1:28:00 condition%1:26:00
0.9845	man%1:18:00	0.9824	position%1:15:00	0.9800	form%1:10:00	0.9770	light%1:06:00
0.9845	attempt%1:04:02	0.9824	care%1:09:00	0.9800	passion%1:12:00	0.9770	breast%1:08:00
0.9844 0.9844	interaction%1:04:00 phase%1:28:00	0.9823	generation%1:14:01 dog%1:18:01	0.9800	migration%1:14:00 idea%1:09:00	0.9770 0.9770	country%1:14:00 foot%1:23:00
0.9844	level%1:07:00	0.9822	spring%1:06:00	0.9797	perspective%1:09:00	0.9770	score%1:10:00
0.9844	outlet%1:06:02	0.9821	president%1:18:01	0.9797	region%1:08:00	0.9769	account%1:10:03
0.9843 0.9843	knot%1:06:00 campaign%1:04:02	0.9820	past%1:28:01 brand%1:09:00	0.9797 0.9797	need%1:26:00 attention%1:04:01	0.9769 0.9768	circumstance%1:26:01 detail%1:24:00
0.9843	career%1:04:00	0.9819	assumption%1:09:00	0.9797	patient%1:10:00	0.9768	question%1:10:01
0.9843	advantage%1:23:00	0.9818	control%1:07:00	0.9794	protection%1:06:00	0.9767	release%1:04:01
0.9843 0.9841	word%1:10:00 thing%1:26:00	0.9818	reaction%1:09:00 power%1:19:00	0.9794 0.9794	history%1:28:00 quantity%1:07:00	0.9765 0.9765	contract%1:10:01 executive%1:14:01
0.9841	method%1:09:00	0.9818	bay%1:17:00	0.9793	mode%1:26:00	0.9765	version%1:10:01
0.9841	party%1:14:01	0.9818	rise%1:11:00	0.9793	problem%1:26:00	0.9764	margin%1:07:00
0.9839 0.9839	lady%1:18:02 place%1:15:00	0.9818	review%1:09:00 atmosphere%1:23:00	0.9792 0.9792	pressure%1:07:00 cent%1:23:00	0.9763 0.9763	area%1:15:01 disco%1:06:00
0.9838	offer%1:10:01	0.9817	fear%1:12:01	0.9792	threat%1:10:00	0.9762	critic%1:18:01
0.9838	characteristic%1:09:00	0.9817	player%1:18:01	0.9792	owner%1:18:02	0.9762	writer%1:18:00
0.9838 0.9836	understanding%1:10:00	0.9817 0.9816	resource%1:07:00 evidence%1:10:01	0.9791 0.9790	type%1:09:00	0.9761 0.9760	america%1:15:00 altar%1:06:01
0.9836	issue%1:09:01 representation%1:06:00	0.9816	leaflet%1:20:00	0.9790	value%1:09:00 test%1:04:02	0.9760	circus%1:04:00
0.9835	statement%1:10:00	0.9816	member%1:18:00	0.9789	capital%1:21:00	0.9760	ownership%1:04:00
0.9835	territory%1:15:00	0.9816	pupil%1:08:00	0.9788	service%1:04:08	0.9759	noise%1:09:00
0.9758 0.9758	discovery%1:10:00 activity%1:04:00	0.9711	use%1:04:00 society%1:14:00	0.9665 0.9665	programme%1:10:05 vote%1:04:01	0.9606 0.9606	group%1:03:00 situation%1:26:01
0.9756	society%1:14:01	0.9708	habit%1:04:02	0.9664	course%1:14:00	0.9606	figure%1:08:00
0.9754	talent%1:09:00	0.9708	language%1:10:01	0.9664	night%1:28:01	0.9606	official%1:18:00
0.9754 0.9754	war%1:04:00 person%1:03:00	0.9707	retention%1:04:00 circle%1:14:00	0.9662 0.9661	future%1:10:00 length%1:07:01	0.9604 0.9602	stage%1:26:00 march%1:04:00
0.9753	center%1:15:01	0.9706	treasury%1:21:00	0.9661	order%1:10:03	0.9602	volume%1:07:03
0.9753	computer%1:18:00	0.9705	assertion%1:10:00	0.9661	earth%1:27:00	0.9601	church%1:06:00
0.9753 0.9752	will%1:09:00 dose%1:23:00	0.9705	carnival%1:04:02 door%1:06:01	0.9661 0.9660	life%1:26:01 arm%1:06:03	0.9601 0.9600	role%1:09:00 source%1:10:00
0.9751	phase%1:26:00	0.9701	term%1:28:00	0.9660	thought%1:09:00	0.9599	cent%1:21:00
0.9750	stability%1:26:00	0.9699	proposal%1:10:02	0.9659	law%1:14:00	0.9596	seat%1:08:00
0.9749 0.9749	town%1:14:00 repression%1:22:00	0.9699	condition%1:10:01 set%1:14:00	0.9656 0.9656	state%1:15:01 aspect%1:07:02	0.9596 0.9595	project%1:09:00 reduction%1:22:00
0.9749	progress%1:04:00	0.9696	part%1:24:00	0.9656	system%1:06:00	0.9593	block%1:06:00
0.9748	student%1:18:00	0.9694	money%1:21:02	0.9656	eye%1:09:00	0.9591	gold%1:07:00
0.9747 0.9746	publication%1:10:00 effect%1:19:00	0.9694	hour%1:28:01 act%1:03:00	0.9654	perspective%1:07:00 banking%1:04:00	0.9591 0.9590	people%1:14:00 piece%1:06:05
0.9745	offer%1:10:00	0.9694	voice%1:10:00	0.9651	charge%1:10:00	0.9589	issue%1:10:00
0.9744	table%1:06:01	0.9693	diet%1:14:00	0.9648	economy%1:09:01	0.9587	version%1:09:01
0.9743 0.9742	process%1:04:00 bill%1:10:01	0.9693	hunter%1:18:01 fund%1:21:00	0.9646 0.9646	responsibility%1:26:00 variety%1:07:00	0.9585 0.9583	practice%1:04:02 reason%1:10:01
0.9739	congress%1:14:00	0.9691	document%1:06:00	0.9644	temperature%1:09:00	0.9578	number%1:23:00
0.9739	record%1:06:00	0.9690	end%1:15:00	0.9643	virtue%1:07:03	0.9577	president%1:18:04
0.9738 0.9738	justice%1:04:00 government%1:14:00	0.9690 0.9689	head%1:05:00 period%1:28:00	0.9639 0.9637	infrastructure%1:06:00 day%1:28:00	0.9574 0.9572	philosophy%1:09:00 interest%1:07:01
0.9737	top%1:15:00	0.9687	background%1:09:00	0.9632	control%1:24:00	0.9569	washington%1:15:00
0.9737	current%1:11:00	0.9686	handful%1:23:01	0.9631	glass%1:06:00	0.9566	fate%1:18:00
0.9734 0.9734	effort%1:04:01 union%1:15:00	0.9686	director%1:18:03 left%1:14:00	0.9629 0.9629	cat%1:18:01 horn%1:05:01	0.9565 0.9564	support%1:04:04 chart%1:06:00
0.9734	today%1:28:01	0.9685	driver%1:18:02	0.9627	discussion%1:10:00	0.9562	position%1:15:02
0.9732	europe%1:17:00	0.9684	week%1:28:01	0.9627	mg%1:27:00	0.9560	metal%1:27:01
0.9730 0.9730	element%1:06:00 water%1:17:00	0.9684 0.9679	violence%1:07:00 company%1:14:01	0.9626 0.9626	pilot%1:18:01 debate%1:10:00	0.9560 0.9560	dollar%1:21:00 male%1:18:00
0.9729	pair%1:23:00	0.9679	fight%1:04:02	0.9623	strategy%1:09:01	0.9558	journal%1:10:00
0.9728	perimeter%1:25:01	0.9677	ground%1:16:00	0.9623	stake%1:10:00	0.9558	london%1:18:00
0.9727 0.9725	box%1:06:02 path%1:06:00	0.9677	leadership%1:14:00 window%1:06:01	0.9623 0.9623	interaction%1:19:00 month%1:28:01	0.9557 0.9557	increase%1:11:00 information%1:09:00
0.9723	cup%1:23:01	0.9676	race%1:11:00	0.9623	unit%1:24:00	0.9557	fairness%1:07:00
0.9722	conference%1:14:01	0.9674	3d%1:09:00	0.9621	success%1:04:00	0.9554	tie%1:26:01
0.9721	estimate%1:04:01	0.9672	china%1:06:00	0.9621	range%1:15:01	0.9552	center%1:06:02
0.9721 0.9720	response%1:19:00 examination%1:10:00	0.9672	level%1:26:01 security%1:21:01	0.9621	game%1:04:03 announcement%1:10:00	0.9552 0.9552	trouble%1:09:00 governor%1:06:00
0.9720	art%1:04:00	0.9670	status%1:26:01	0.9617	concern%1:12:01	0.9550	work%1:04:00
0.9718	product%1:06:01	0.9670	technology%1:09:00	0.9614	list%1:07:00	0.9548	job%1:04:01
0.9717 0.9717	city%1:15:00 fire%1:04:00	0.9670 0.9669	difference%1:11:00 office%1:14:01	0.9614 0.9612	pattern%1:04:00 need%1:17:00	0.9548 0.9545	period%1:28:02 capability%1:26:00
0.9716	wave%1:04:02	0.9669	opposite%1:10:00	0.9610	competition%1:11:00	0.9544	judge%1:18:01
0.9714	ring%1:25:00	0.9666	english%1:18:00	0.9608	world%1:17:01	0.9543	actor%1:18:01
0.9714	population%1:14:01	0.9666	pier%1:06:02	0.9606	bank%1:14:00	0.9542	bar%1:06:05

AP_c^\star	sense concept	$ AP_c^{\star} $	sense concept	$ AP_c^{\star} $	sense concept
0.9541	word%1:10:03	0.9370	leader%1:06:00	0.9168	research%1:09:00
0.9540	politician%1:18:01	0.9366	student%1:18:01	0.9167	cause%1:10:00
0.9538	rate%1:21:00	0.9366	front%1:15:01	0.9162	farmer%1:18:01
0.9536	operation%1:04:06	0.9362	circumstance%1:26:02	0.9159	cleveland%1:18:00
0.9534	color%1:07:03	0.9355	community%1:21:00	0.9155	side%1:14:00
0.9532	participant%1:18:01	0.9341	order%1:07:01	0.9153	show%1:10:03
0.9530	value%1:07:00	0.9338	hope%1:12:01	0.9149	story%1:10:00
0.9518	lady%1:18:01	0.9336	cost%1:07:00	0.9145	change%1:24:00
0.9518	victim%1:18:00	0.9333	company%1:14:03	0.9116	cell%1:03:00
0.9515	education%1:09:00	0.9333	statement%1:10:02	0.9109	extent%1:07:00
0.9514	name%1:26:00	0.9323	series%1:10:01	0.9069	law%1:10:00
0.9513	family%1:14:00	0.9312	air%1:27:00	0.9058	industry%1:04:00
0.9506	line%1:14:03	0.9310	regard%1:09:01	0.9054	altar%1:06:00
0.9505	paper%1:10:01	0.9305	france%1:18:00	0.9051	response%1:04:01
0.9502	stone%1:06:00	0.9299	relation%1:04:01	0.9049	system%1:14:00
0.9501	book%1:06:00	0.9293	time%1:11:00	0.9009	decade%1:23:00
0.9498	moon%1:17:02	0.9292	performance%1:04:01	0.8987	career%1:04:01
0.9498	view%1:09:02	0.9290	america%1:17:00	0.8977	government%1:04:00
0.9495	opponent%1:18:00	0.9283	point%1:09:00	0.8976	history%1:10:00
0.9495	movement%1:04:04	0.9282	policy%1:10:00	0.8951	standing%1:26:00
0.9494	grade%1:26:00	0.9280	will%1:09:01	0.8950	process%1:09:00
0.9493	damage%1:11:01	0.9276	selection%1:14:00	0.8939	day%1:28:03
0.9493	club%1:14:00	0.9274	loan%1:10:00	0.8938	amount%1:07:00
0.9484	sale%1:04:02	0.9271	case%1:26:00	0.8928	service%1:04:00
0.9476	foundation%1:14:00	0.9268	structure%1:07:00	0.8926	theory%1:09:00
0.9469	child%1:18:01	0.9263	meeting%1:14:01	0.8867	basis%1:09:00
0.9467	file%1:14:00	0.9257	body%1:14:00	0.8861	city%1:15:01
0.9466	month%1:28:00	0.9255	age%1:28:02	0.8790	people%1:14:01
0.9464	commitment%1:07:01	0.9255	car%1:06:01	0.8787	high%1:07:00
0.9461	constituent%1:18:00	0.9254	end%1:28:00	0.8779	one%1:09:00
0.9457	diner%1:06:00	0.9252	class%1:14:03	0.8734	area%1:09:00
0.9454	impact%1:19:00	0.9250	player%1:18:02	0.8732	house%1:14:01
0.9453	example%1:09:02	0.9246	relative%1:05:00	0.8693	world%1:14:01
0.9449	nature%1:07:02	0.9246	street%1:06:01	0.8668	state%1:03:00
0.9447	event%1:26:00	0.9243	rule%1:09:01	0.8640	man%1:18:03
0.9438	type%1:18:00	0.9226	activity%1:26:00	0.8637	standing%1:10:00
0.9435	plan%1:09:01	0.9225	american%1:10:00	0.8582	outpost%1:14:00
0.9425	member%1:24:00	0.9224	reference%1:10:03	0.8578	form%1:09:01
0.9421	letter%1:10:01	0.9220	institution%1:06:00	0.8508	work%1:06:00
0.9420	kid%1:27:00	0.9218	development%1:22:02	0.8481	use%1:07:00
0.9416	addition%1:04:02	0.9217	part%1:06:00	0.8478	canon%1:18:00
0.9414	result%1:10:00	0.9206	program%1:09:01	0.8242	year%1:28:02
0.9413	claim%1:10:02	0.9206	method%1:04:00	0.8198	ringer%1:18:02
0.9390	enterprise%1:04:00	0.9203	place%1:15:04	0.7439	time%1:28:05
0.9387	fund%1:21:01	0.9197	investigation%1:04:00		
0.9386	adaptation%1:22:00	0.9193	thing%1:04:00		
0.9385	characteristic%1:07:00	0.9190	way%1:04:01		
0.9384	group%1:27:00	0.9189	country%1:15:00		
0.9380	resident%1:18:01	0.9180	effect%1:07:00		
0.9374	net%1:06:01	0.9168	material%1:10:00		
3.22.7		1 3.51.00		1	

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

AP_c^\star	homograph concept	AP_c^{\star}	homograph concept	AP_c^{\star}	homograph concept
0.9984	killer%1:26:00 VS. killer%1:18:00	0.8459	phase%1:26:00 VS. phase%1:28:00	0.6803	violence%1:07:00 VS. violence%1:04:01
0.9972 0.9956	suspension%1:28:00 VS. suspension%1:27:00 margin%1:07:00 VS. margin%1:25:00	0.8457 0.8404	extent%1:07:00 VS. extent%1:26:00 plot%1:15:00 VS. plot%1:09:00	0.6762 0.6751	history%1:10:00 VS. history%1:28:00 office%1:14:01 VS. office%1:06:00
0.9928	log%1:10:01 VS. log%1:27:01	0.8389	role%1:09:00 VS. role%1:04:00	0.6733	quantity%1:07:00 VS. quantity%1:03:00
0.9911 0.9911	round%1:28:01 VS. round%1:06:01 lead%1:27:00 VS. lead%1:07:02	0.8323 0.8312	area%1:09:00 VS. area%1:15:01 house%1:14:01 VS. house%1:06:00	0.6721 0.6712	use%1:07:00 VS. use%1:04:00 interest%1:07:01 VS. interest%1:09:00
0.9882	relative%1:05:00 VS. relative%1:18:00	0.8295	arm%1:06:03 VS. arm%1:08:00	0.6707	session%1:28:00 VS. session%1:10:00
0.9875 0.9871	plane%1:25:00 VS. plane%1:06:01 stake%1:10:00 VS. stake%1:21:02	0.8254 0.8192	charge%1:10:00 VS. charge%1:04:01 amount%1:07:00 VS. amount%1:21:00	0.6672 0.6660	method%1:04:00 VS. method%1:09:00 bird%1:13:00 VS. bird%1:05:00
0.9857	card%1:10:01 VS. card%1:06:00	0.8146	american%1:10:00 VS. american%1:18:00	0.6655	crisis%1:11:00 VS. crisis%1:26:00
0.9840 0.9840	patient%1:10:00 VS. patient%1:18:00 heart%1:08:00 VS. heart%1:09:00	0.8143 0.8137	times%1:04:00 VS. times%1:28:01 crystal%1:06:02 VS. crystal%1:27:00	0.6640 0.6635	march%1:04:00 VS. march%1:28:00 deal%1:10:00 VS. deal%1:04:02
0.9815 0.9807	duck%1:23:00 VS. duck%1:05:00 diet%1:14:00 VS. diet%1:13:00	0.8118 0.8063	commerce%1:14:00 VS. commerce%1:04:00 volume%1:07:03 VS. volume%1:23:00	0.6605 0.6526	attention%1:04:01 VS. attention%1:09:00 medicine%1:06:00 VS. medicine%1:09:00
0.9794	bond%1:21:02 VS. bond%1:19:00	0.8055	visit%1:14:00 VS. visit%1:04:02	0.6520	campaign%1:04:02 VS. campaign%1:11:00
0.9788 0.9780	trainer%1:06:00 VS. trainer%1:18:00 china%1:06:00 VS. china%1:15:00	0.8034 0.8030	addition%1:04:02 VS. addition%1:06:00 cause%1:10:00 VS. cause%1:11:00	0.6518 0.6485	gas%1:27:00 VS. gas%1:26:00 machine%1:18:00 VS. machine%1:06:00
0.9765	sum%1:09:01 VS. sum%1:21:00	0.8020	frequency%1:24:00 VS. frequency%1:28:00	0.6451	part%1:06:00 VS. part%1:24:00
0.9764 0.9741	governor%1:06:00 VS. governor%1:18:00 delivery%1:11:00 VS. delivery%1:04:04	0.8018 0.8016	nightmare%1:09:00 VS. nightmare%1:26:00 detail%1:24:00 VS. detail%1:09:00	0.6422 0.6409	representation%1:06:00 VS. representation%1:09:00 drink%1:04:00 VS. drink%1:13:04
0.9674	region%1:08:00 VS. region%1:15:00	0.8007	chair%1:04:00 VS. chair%1:06:00	0.6381	security%1:21:01 VS. security%1:26:00
0.9668 0.9618	current%1:11:00 VS. current%1:19:01 spring%1:06:00 VS. spring%1:28:00	0.8001 0.7994	whole%1:03:00 VS. whole%1:09:00 increase%1:11:00 VS. increase%1:23:00	0.6248 0.6228	leadership%1:14:00 VS. leadership%1:04:00 obstacle%1:06:00 VS. obstacle%1:09:00
0.9604	pupil%1:08:00 VS. pupil%1:18:00	0.7986	light%1:06:00 VS. light%1:19:00	0.6176	decade%1:23:00 VS. decade%1:28:00
0.9567 0.9547	mg%1:27:00 VS. mg%1:23:00 center%1:06:02 VS. center%1:15:01	0.7961 0.7947	fate%1:18:00 VS. fate%1:11:00 liquor%1:27:00 VS. liquor%1:13:00	0.6083 0.6057	reason%1:10:01 VS. reason%1:16:00 dispute%1:04:00 VS. dispute%1:10:00
0.9547	space%1:25:00 VS. space%1:03:00	0.7928	reaction%1:09:00 VS. reaction%1:22:00	0.6044	maintenance%1:21:00 VS. maintenance%1:04:00
0.9524 0.9487	loan%1:10:00 VS. loan%1:21:00 activity%1:26:00 VS. activity%1:04:00	0.7920 0.7882	state%1:03:00 VS. state%1:15:01 agent%1:18:02 VS. agent%1:17:00	0.6043 0.5968	sound%1:09:00 VS. sound%1:07:00 parish%1:15:00 VS. parish%1:14:00
0.9469 0.9399	adaptation%1:22:00 VS. adaptation%1:10:00 response%1:04:01 VS. response%1:19:00	0.7876 0.7862	intervention%1:10:00 VS. intervention%1:04:00 america%1:17:00 VS. america%1:15:00	0.5954 0.5947	noise%1:09:00 VS. noise%1:11:00
0.9395	reduction%1:22:00 VS. reduction%1:04:00	0.7835	estimate%1:04:01 VS. estimate%1:09:00	0.5939	aspect%1:07:02 VS. aspect%1:09:00 system%1:14:00 VS. system%1:06:00
0.9385 0.9384	value%1:07:00 VS. value%1:09:00 ministry%1:06:00 VS. ministry%1:14:01	0.7810 0.7800	voice%1:10:00 VS. voice%1:07:00 tie%1:26:01 VS. tie%1:06:01	0.5935 0.5897	concern%1:12:01 VS. concern%1:09:00 show%1:10:03 VS. show%1:04:00
0.9371	craft%1:06:00 VS. craft%1:04:00	0.7785	executive%1:14:01 VS. executive%1:18:00	0.5874	chart%1:06:00 VS. chart%1:10:00
0.9343 0.9330	border%1:25:00 VS. border%1:15:00 interaction%1:19:00 VS. interaction%1:04:00	0.7775 0.7774	side%1:14:00 VS. side%1:15:02 trip%1:26:00 VS. trip%1:04:00	0.5851 0.5846	signal%1:16:00 VS. signal%1:10:00 dollar%1:21:00 VS. dollar%1:23:00
0.9329	level%1:26:01 VS. level%1:07:00	0.7773	act%1:03:00 VS. act%1:10:01	0.5823	return%1:04:01 VS. return%1:10:01
0.9319 0.9299	solution%1:10:00 VS. solution%1:27:00 selection%1:14:00 VS. selection%1:04:00	0.7755 0.7755	change%1:24:00 VS. change%1:11:00 difference%1:11:00 VS. difference%1:07:00	0.5800 0.5786	book%1:06:00 VS. book%1:10:00 protection%1:06:00 VS. protection%1:04:00
0.9296	path%1:06:00 VS. path%1:04:00	0.7737	cleveland%1:18:00 VS. cleveland%1:15:00	0.5778	pleasure%1:09:00 VS. pleasure%1:12:00
0.9261 0.9248	score%1:10:00 VS. score%1:09:00 right%1:15:00 VS. right%1:07:00	0.7725 0.7718	authority%1:18:01 VS. authority%1:07:00 process%1:09:00 VS. process%1:04:00	0.5776 0.5768	computer%1:18:00 VS. computer%1:06:00 youth%1:14:00 VS. youth%1:18:00
0.9244	course%1:14:00 VS. course%1:04:01	0.7673	town%1:14:00 VS. town%1:15:00	0.5760	cup%1:23:01 VS. cup%1:06:00
0.9190 0.9161	interval%1:09:00 VS. interval%1:28:00 cycle%1:14:00 VS. cycle%1:28:00	0.7668 0.7655	commission%1:21:00 VS. commission%1:14:00 cloud%1:17:00 VS. cloud%1:19:01	0.5747 0.5702	copy%1:06:00 VS. copy%1:10:00 competition%1:11:00 VS. competition%1:24:01
0.9157	angle%1:09:00 VS. angle%1:25:00	0.7646	resource%1:07:00 VS. resource%1:21:00	0.5684	dinner%1:14:00 VS. dinner%1:13:00
0.9143 0.9109	basis%1:09:00 VS. basis%1:24:00 file%1:14:00 VS. file%1:10:00	0.7635 0.7634	stage%1:26:00 VS. stage%1:28:00 one%1:09:00 VS. one%1:23:00	0.5634 0.5612	standing%1:10:00 VS. standing%1:26:00 cost%1:07:00 VS. cost%1:21:00
0.9106	order%1:07:01 VS. order%1:10:03	0.7596	isolation%1:12:00 VS. isolation%1:26:00	0.5579	cent%1:21:00 VS. cent%1:23:00
0.9098 0.9097	obligation%1:26:00 VS. obligation%1:04:00 loss%1:22:00 VS. loss%1:21:01	0.7572 0.7504	term%1:28:00 VS. term%1:10:00 rank%1:26:00 VS. rank%1:14:00	0.5573 0.5569	thing%1:04:00 VS. thing%1:26:00 france%1:18:00 VS. france%1:15:00
0.9071 0.9061	record%1:06:00 VS. record%1:10:03 personality%1:18:00 VS. personality%1:07:00	0.7494 0.7491	wave%1:04:02 VS. wave%1:11:01 pair%1:23:00 VS. pair%1:14:01	0.5564 0.5524	ground%1:16:00 VS. ground%1:17:00 institution%1:06:00 VS. institution%1:14:00
0.9050	horn%1:05:01 VS. horn%1:06:06	0.7475	cat%1:18:01 VS. cat%1:05:00	0.5482	range%1:15:01 VS. range%1:07:00
0.9021 0.8994	operator%1:18:00 VS. operator%1:24:00 examination%1:10:00 VS. examination%1:04:00	0.7446 0.7440	address%1:15:00 VS. address%1:10:04 heel%1:08:00 VS. heel%1:06:00	0.5449 0.5312	world%1:14:01 VS. world%1:17:01 flow%1:28:00 VS. flow%1:11:00
0.8978	bank%1:14:00 VS. bank%1:17:01	0.7377	$understanding\%1:10:00\ VS.\ understanding\%1:09:01$	0.5269	circus%1:04:00 VS. circus%1:14:00
0.8964 0.8964	repression%1:22:00 VS. repression%1:26:00 list%1:07:00 VS. list%1:10:00	0.7376 0.7351	care%1:09:00 VS. care%1:04:01 number%1:23:00 VS. number%1:07:00	0.5264 0.5240	influence%1:04:00 VS. influence%1:07:00 market%1:14:00 VS. market%1:04:00
0.8955	3d%1:09:00 VS. 3d%1:10:00	0.7345	height%1:26:00 VS. height%1:07:00	0.5209	decision%1:09:00 VS. decision%1:04:00
0.8954	suit%1:04:00 VS. suit%1:06:00 left%1:14:00 VS. left%1:15:00	0.7319 0.7305	goal%1:15:00 VS. goal%1:09:00 london%1:18:00 VS. london%1:15:00	0.5145 0.5112	broadcaster%1:06:00 VS. broadcaster%1:18:00 performance%1:04:01 VS. performance%1:10:00
0.8939	cell%1:03:00 VS. cell%1:06:03	0.7293	dog%1:18:01 VS. dog%1:05:00	0.5100	stone%1:06:00 VS. stone%1:17:00
0.8927 0.8925	shock%1:04:01 VS. shock%1:12:01 name%1:26:00 VS. name%1:10:00	0.7285 0.7281	sunday%1:18:00 VS. sunday%1:28:00 discovery%1:10:00 VS. discovery%1:04:00	0.5085 0.5070	appearance%1:11:00 VS. appearance%1:07:00 research%1:09:00 VS. research%1:04:00
0.8902	pocket%1:25:00 VS. pocket%1:06:00	0.7271	test%1:04:02 VS. test%1:09:02	0.4946	threat%1:10:00 VS. threat%1:26:00
0.8894 0.8861	future%1:10:00 VS. future%1:28:00 advantage%1:23:00 VS. advantage%1:07:00	0.7270 0.7267	guy%1:06:01 VS. guy%1:18:00 category%1:09:02 VS. category%1:14:00	0.4884 0.4871	wish%1:10:00 VS. wish%1:12:00 kid%1:27:00 VS. kid%1:18:00
0.8846 0.8815	chamber%1:08:00 VS. chamber%1:06:00 retirement%1:04:00 VS. retirement%1:26:00	0.7262 0.7262	information%1:09:00 VS. information%1:10:00 poster%1:18:00 VS. poster%1:10:00	0.4854 0.4850	challenge%1:10:00 VS. challenge%1:26:00 characteristic%1:07:00 VS. characteristic%1:09:00
0.8802	phone%1:10:00 VS. phone%1:06:00	0.7247	step%1:23:00 VS. step%1:04:02	0.4800	usa%1:14:00 VS. usa%1:15:00
0.8789 0.8788	age%1:28:02 VS. age%1:07:00 table%1:06:01 VS. table%1:14:00	0.7245 0.7236	grade%1:26:00 VS. grade%1:14:00 triumph%1:12:00 VS. triumph%1:11:00	0.4744 0.4732	industry%1:04:00 VS. industry%1:14:00 face%1:07:03 VS. face%1:08:00
0.8787	oil%1:06:01 VS. oil%1:27:00	0.7227	connecticut%1:17:00 VS. connecticut%1:15:00	0.4680	eye%1:09:00 VS. eye%1:08:00
0.8762 0.8757	power%1:19:00 VS. power%1:07:00 gold%1:07:00 VS. gold%1:21:00	0.7207 0.7185	variety%1:07:00 VS. variety%1:14:01 blood%1:07:00 VS. blood%1:08:00	0.4643 0.4563	prayer%1:10:02 VS. prayer%1:04:00 distinction%1:26:00 VS. distinction%1:09:00
0.8755	seat%1:08:00 VS. seat%1:15:01	0.7163	involvement%1:24:00 VS. involvement%1:04:00	0.4468	document%1:06:00 VS. document%1:10:00
0.8737 0.8727	responsibility%1:26:00 VS. responsibility%1:04:00 bonus%1:21:00 VS. bonus%1:09:00	0.7157 0.7151	art%1:04:00 VS. art%1:06:00 favor%1:07:00 VS. favor%1:04:00	0.4423 0.4179	disco%1:06:00 VS. disco%1:10:00 investigation%1:04:00 VS. investigation%1:09:00
0.8722	time%1:28:05 VS. time%1:11:00	0.7103	success%1:04:00 VS. success%1:11:00	0.4126	justice%1:04:00 VS. justice%1:07:00
0.8720 0.8714	administration%1:14:00 VS. administration%1:04:00 dose%1:23:00 VS. dose%1:06:00	0.7063 0.7050	canon%1:18:00 VS. canon%1:10:00 capability%1:26:00 VS. capability%1:07:00	0.4088 0.3976	inspiration%1:06:00 VS. inspiration%1:09:02 brand%1:09:00 VS. brand%1:10:00
0.8691	pattern%1:04:00 VS. pattern%1:09:00	0.7044	evidence%1:10:01 VS. evidence%1:09:00	0.3917	assumption%1:09:00 VS. assumption%1:10:00
0.8684 0.8670	perspective%1:07:00 VS. perspective%1:09:00 brazil%1:13:00 VS. brazil%1:15:00	0.7033 0.7006	impact%1:19:00 VS. impact%1:11:00 factor%1:09:00 VS. factor%1:11:00	0.3870 0.3861	hell%1:11:00 VS. hell%1:15:01 country%1:15:00 VS. country%1:14:00
0.8670	pet%1:18:00 VS. pet%1:05:00	0.6991	identity%1:09:00 VS. identity%1:07:00	0.3816	government%1:04:00 VS. government%1:14:00
0.8665 0.8662	need%1:17:00 VS. need%1:26:00 leader%1:06:00 VS. leader%1:18:00	0.6983 0.6951	glass%1:06:00 VS. glass%1:27:00 migration%1:14:00 VS. migration%1:04:00	0.3808 0.3779	help%1:18:00 VS. help%1:04:00 project%1:09:00 VS. project%1:04:00
0.8642	temperature%1:09:00 VS. temperature%1:07:00	0.6935	control%1:24:00 VS. control%1:07:00	0.3775	insight%1:12:00 VS. insight%1:09:02
0.8642 0.8617	fire%1:04:00 VS. fire%1:11:00 rate%1:21:00 VS. rate%1:28:00	0.6926 0.6922	development%1:22:02 VS. development%1:04:01 issue%1:10:00 VS. issue%1:09:01	0.3738 0.3728	thanks%1:04:00 VS. thanks%1:10:00 negotiation%1:04:00 VS. negotiation%1:10:00
0.8575	gender%1:07:00 VS. gender%1:10:00	0.6889	ownership%1:04:00 VS. ownership%1:21:00	0.3668	behalf%1:07:00 VS. behalf%1:04:00
0.8562 0.8553	material%1:10:00 VS. material%1:27:00 union%1:15:00 VS. union%1:14:01	0.6887 0.6883	limit%1:28:00 VS. limit%1:07:00 rhythm%1:07:01 VS. rhythm%1:10:01	0.3621 0.3585	backing%1:06:00 VS. backing%1:04:00 technology%1:09:00 VS. technology%1:04:00
0.8512 0.8472	relation%1:04:01 VS. relation%1:03:00 background%1:09:00 VS. background%1:07:00	0.6867 0.6858	water%1:17:00 VS. water%1:27:00 source%1:10:00 VS. source%1:15:00	0.3484 0.2936	sin%1:04:00 VS. sin%1:07:00 surprise%1:11:00 VS. surprise%1:12:00
0.8469	circle%1:14:00 VS. circle%1:25:00	0.6852	boost%1:07:00 VS. boost%1:04:00	0.2730	Sulprise 701.11.00 v.S. Sulprise 701:12:00
0.8467 0.8467	condition%1:10:01 VS. condition%1:26:00 paper%1:10:01 VS. paper%1:27:00	0.6811 0.6807	bronze%1:06:00 VS. bronze%1:27:00 draft%1:19:00 VS. draft%1:21:00		
0.0407	paper /01.10.01 v.s. paper /01.27.00	0.0007	diat./o1.17.00 v 5. diatt/o1.21.00		