A Pruning-Based Deep Learning Approach For Information Retrieval

Master of Science in Engineering in Computer Science

Deep Learning

Sapienza Università di Roma

Speakers

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Task Description

Neural Inverted Index: a unified model replicating the behavior of a conventional index and performing enhanced retrieval by leveraging the power of neural networks.

→ Our **focus** is on **optimizing a DSI model**, denoted as f, which takes a query q as input and produces a ranked list of document IDs.

Dataset

- We used the **MS MARCO** dataset through the Pyserini toolkit:
  - Select the **most relevant K document IDs** for each query of the dataset, and use this data for training the model.
  - Select the **most relevant 1000 document IDs** only for the **Recall@1000** metric computation (see later).
- We used the **T5 tokenizer** for tokenizing both the queries and the document IDs.

Evaluation Metrics

We assessed our model using the following **metrics**:

- **MAP (Mean Average Precision):** the mean of the average precision scores from a set of queries.

- **Recall@1000:** the proportion of relevant document IDs found in the top-1000 results.

Baseline

- We used a **pre-trained T5** model from Hugging Face, embedded in a Pytorch Lightning module.
- We have **fine-tuned** all the layers of the pre-trained T5 model on our task, so that the model was able to predict a ranked list of document IDs, given an input query.
- We have considered **three versions** of the Hugging Face T5 model, having different sizes:
  - T5-large
  - T5-base
  - T5-small

Innovation

→ **Our approach:** employ the **Train-Prune-Recovery strategy** on the proposed baseline in order to let the model work in a resource-constrained environment.

- In particular, the pruning:
  - One-shot
  - Unstructured
  - Magnitude-based (L1 norm)

- We have conducted several experiments on the **pruning rate**, in order to find the model with the best metrics performance (see later).

Workflow (1/6)

Goal: comparing different versions of T5 model with their pruned counterparts.

- T5-large: Google Colab limitations (GPU RAM)

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Workflow (2/6)

➢ T5-base:

Table 1: Baseline *t5-base*

K	Batch size	Epochs	Learning rate	Patience	Test loss	MAP	Recall@1000
25	16	30	0.001	5	3.514	0.00100	0.0
20	16	30	0.001	5	4.628	0.00135	4.00E-05
5	8	20	0.001	∞	8.323	0.00352	5.00E-05
5	**8**	**23**	**0.001**	∞	**8.604**	**0.00563**	**0.00011**

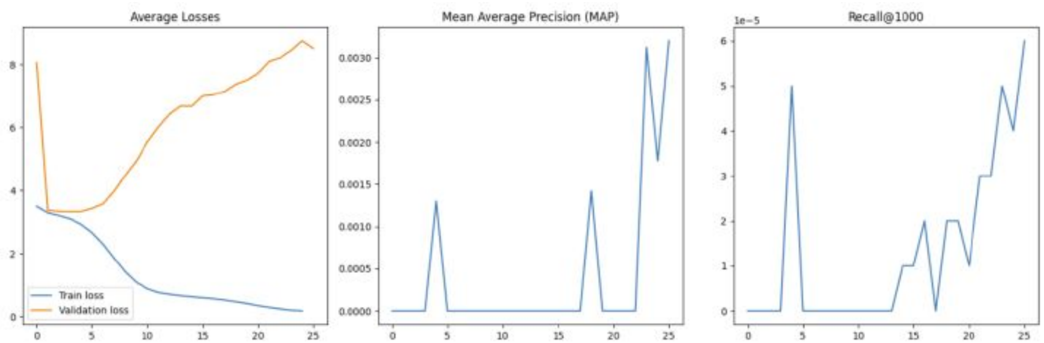


Figure 1: Plots of the best baseline *t5-base* result.

Workflow (3/6)

- T5-base observations:
  - We could train for **fewer epochs** with a **large K.**
  - **Performance** on metrics **increases** as the number of **training epochs increases**: **epoch-wise double descent?**
  - Due to Colab limitations, we **couldn't apply** the Train-Prune-Recovery strategy.

Workflow (4/6)

- T5-small:

Table 2: Baseline *t5-small*

K	Batch size	Epochs	Learning rate	Patience	Test loss	MAP	Recall@1000
25	8	20	0.001	∞	8.558	0.0	0.0
10	8	50	0.001	∞	11.197	0.00100	0.0
5	**8**	**25**	**0.001**	∞	**9.339**	**0.00119**	**2.00E-05**

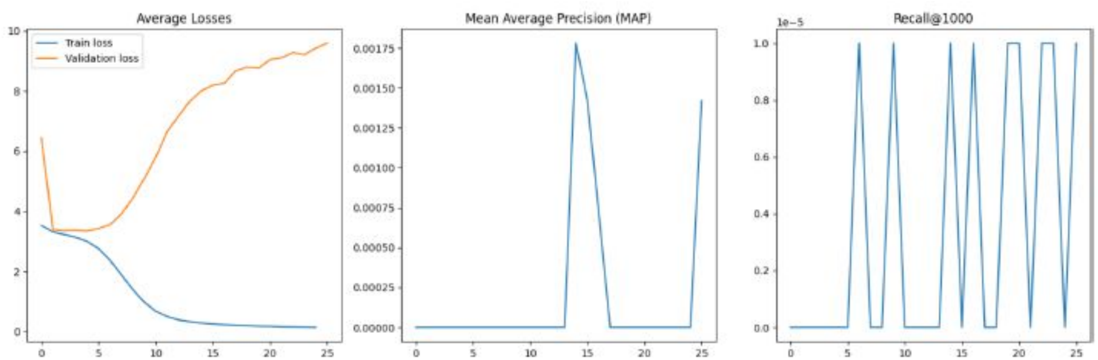


Figure 2: Plots of the best baseline *t5-small* result.

Workflow (5/6)

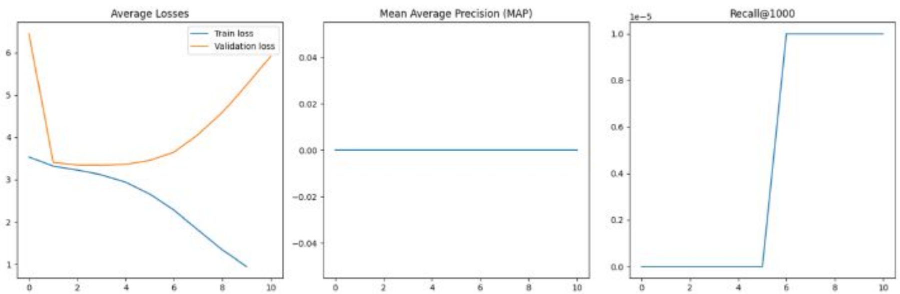
➢ T5-small pruned:

Table 3: Pruned *t5-small*

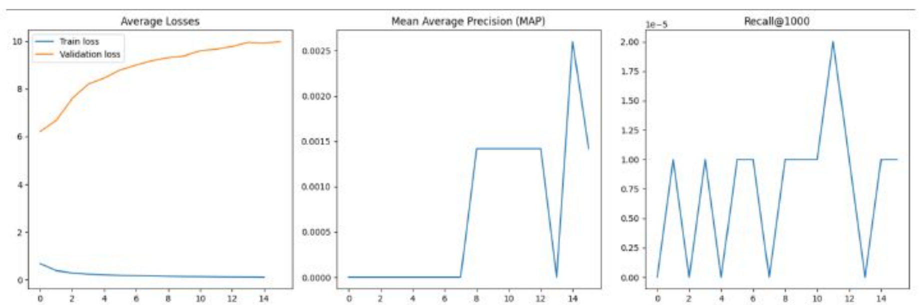
K	Batch size	Epochs (total)	Learning rate	Patience	Pruning rate	Test loss	MAP	Recall@1000
5	8	25	0.001	∞	0.1	9.596	0.00057	2.00E-05
5	8	25	0.001	∞	0.15	9.710	0.00071	1.00E-05
5	**8**	**25**	**0.001**	∞	**0.2**	**9.901**	**0.00214**	**2.00E-05**
5	8	25	0.001	∞	0.25	10.207	0.00062	1.00E-05
5	8	25	0.001	∞	0.3	10.352	0.00211	2.00E-05
5	8	25	0.001	∞	0.4	10.464	0.00071	1.00E-05
5	8	25	0.001	∞	0.5	10.768	0.00167	1.00E-05

Workflow (6/6)

- T5-small pruned:



Non-pruned baseline



Pruned baseline

Conclusions

- The **pruned** T5-small **outperforms on both metrics** the T5-small **baseline** when the pruning rate is 0.2 or 0.3:

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Thanks for your interest!

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