Less is KEN: a Universal and Simple Non-Parametric Pruning Algorithm for Large Language Models

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Abstract

Neural network pruning has become increasingly crucial due to the complexity of these models and their widespread use in various fields. Existing pruning algorithms often suffer from limitations such as architecture specificity, excessive complexity and reliance on demanding calculations, rendering them impractical for real-world applications. This paper introduces KEN: a straightforward, universal and unstructured pruning algorithm based on Kernel Density Estimation (KDE). KEN[1] aims to construct optimized transformers by selectively preserving the most significant parameters while restoring others to their pre-training state. This strategy preserves model performance while enabling storage of only the optimized subnetwork, leading to substantial memory savings. Extensive evaluations across seven different LLMs demonstrate that KEN achieves equal or better performance than their original unpruned versions, with a minimum parameter reduction of 25%. Furthermore, in-depth comparisons with established pruning and PEFT algorithms confirm KEN effectiveness. We further introduce KEN$_{viz}$, an explainable tool that visualizes the optimized model composition achieved by KEN from different points of view.

1 Introduction

Large Language Models (LLMs) have become the best and simplest solution for achieving state-of-the-art results in many natural language processing (NLP) applications. However, the increasing use of neural networks (NNs) and transformers (Vaswani et al., 2017) has resulted in a rise in computational cost due to the complexity of arithmetic calculations, larger matrices and the addition of more layers. Consequently, the weight and structure of these models become more complex, requiring high demands in computation and memory.

[1] Code available at https://github.com/itsmattei/KEN

One of the best approaches to address the overwhelming size of LLMs is to reduce their resources through *pruning algorithms*. These algorithms can eliminate parameters or entire components in a NN, making it lighter without compromising its original performance. Pruning algorithms emerged in parallel with the earliest use of NNs (Mozer and Smolensky, 1989; Janowsky, 1989; LeCun et al., 1989), but they have gained significant importance in the last decade due to the widespread use of these networks in various fields. There are many pruning algorithms in literature (Blalock et al., 2020), each with a unique approach or adapted old algorithms for these new architectures (Benbaki et al., 2023). However, the complexity of neural networks can pose a challenge when creating pruning algorithms, as these may require new complex theorems to make the models lightweight (Dong et al., 2017; Malach et al., 2020). Additionally, existing pruning algorithms often exhibit shortcomings in their completeness (Blalock et al., 2020) and fail to consider a critical aspect: the efficient storage of the pruned result. Some algorithms compress models at runtime but lack mechanisms to preserve the reduced NN for future use. Consequently, most algorithms prioritize the speed of reduction and execution, neglecting this critical final stage essential in resource-limited environments (Yang et al., 2017; Sze et al., 2017).

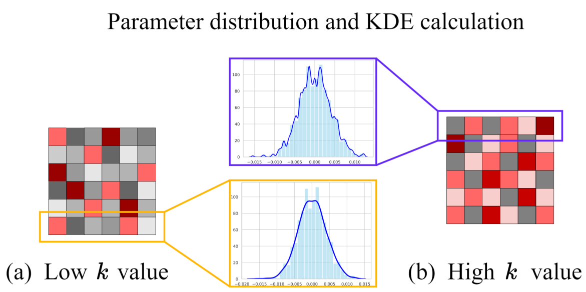

Figure 1: How k value influences the KDE calculation, driving the parameter selection

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This paper presents KEN (**K**ernel density **E**stimator for **N**eural network compression): a universal, simple, magnitude-based transformer pruning algorithm that leverages Kernel Density Estimation (KDE) for parameter pruning. Unlike other pruning methods that rely on minimizing loss functions or exhaustive parameter search, KEN - inspired by the *winning ticket* pruning hypothesis (Frankle and Carbin, 2018) - identifies and retains the most influential parameters using KDEs while resetting the others to their original pre-trained values. This innovative approach streamlines the optimization process by leveraging the natural distribution of model parameters, eliminating any architecture-specific considerations. KEN effectively reduces the size of transformer models by a minimum of 25% without compromising performance. The pruned models consist only of a subnetwork of trained parameters, which can be seamlessly downloaded and injected into its pre-trained version as needed. This feature enables dynamic model reconfiguration and saves significant memory space that would otherwise be required to store the fully trained model. Comparative evaluations demonstrate KEN exceptional capabilities, surpassing existing transformer pruning and PEFT algorithms. Finally, we introduce KEN$_{viz}$: an explainable tool that graphically depicts the optimized model from various perspectives. KEN$_{viz}$ highlights the KEN-selected parameters, their layer-wise differences and neighbor counts for each matrix that made up the analyzed model. Using KEN, we employed a non-parametric method widely used in statistics, to create an efficient and intuitive pruning algorithm. Our approach achieved excellent results in terms of efficiency and performance, making it a practical alternative to other more complex pruning algorithms.

2 Background

Compression algorithms can be summarized in three areas of research: weight pruning (Han et al., 2015; Zhu and Gupta, 2017), quantization (Gong et al., 2014; Zhu et al., 2016) and knowledge distillation (Ba and Caruana, 2014; Kim and Rush, 2016). These techniques aim to make models lighter, but each of them takes a different approach. Weight pruning removes model parameters according to the chosen algorithm and strategy, while quantization reduces the number of bits necessary to represent each parameter. Knowledge distillation, instead, tries to minimize the learned large knowledge of a model into a smaller one without affecting its *validation*.

Focusing on pruning algorithms, there are different approaches depending on the strategy and algorithm adopted. Pruning algorithms can be classified as either *structured* or *unstructured*, based on the approach applied and *magnitude-based* or *impact-based*, according to the algorithm used. Structured pruning (Huang et al., 2018; Wang et al., 2019; Gordon et al., 2020) removes weights in groups, such as entire neurons, filters or layers, while unstructured pruning (Han et al., 2015; Frankle and Carbin, 2018; Lagunas et al., 2021; Benbaki et al., 2023) does not consider any relationship between parameters and selects weights to prune based on their impact or magnitude. Magnitude-based algorithms (Hanson and Pratt, 1988; Mozer and Smolensky, 1989; Gordon et al., 2020) analyze the absolute value of each parameter to determine its importance. In contrast, impact-based algorithms (LeCun et al., 1989; Hassibi and Stork, 1992; Singh and Alistarh, 2020) work on the loss function and its variation caused by removing a parameter. The *winning ticket* hypothesis (Frankle and Carbin, 2018), is a recent advancement in pruning techniques. A *winning ticket* is a subnetwork within a trained model that - when trained in isolation - can achieve performance comparable to the original model even after significant pruning. To identify the winning ticket, a pruning criterion is applied to zero-mask weights and the remaining network is retrained. This process can be repeated multiple times or in a one-shot manner.

3 Related Work

In this section, we present three algorithms that are relevant benchmarks for our proposed algorithm, KEN. These algorithms have some similarities with it: the first two, called FLOP and BMP, are pruning algorithms designed to reduce the size of transformer models by employing algebraic or geometric techniques. The third, LoRA is the SoTA parameter-efficient algorithm for LLMs.

Factorized Low-rank Pruning (FLOP: Wang et al., 2019) is a magnitude-based pruning algorithm that employs matrix factorization to reduce the size of matrices in transformer models. This approach involves decomposing each matrix into rank components, which are then multiplied together to form the original matrix. For attention layers,

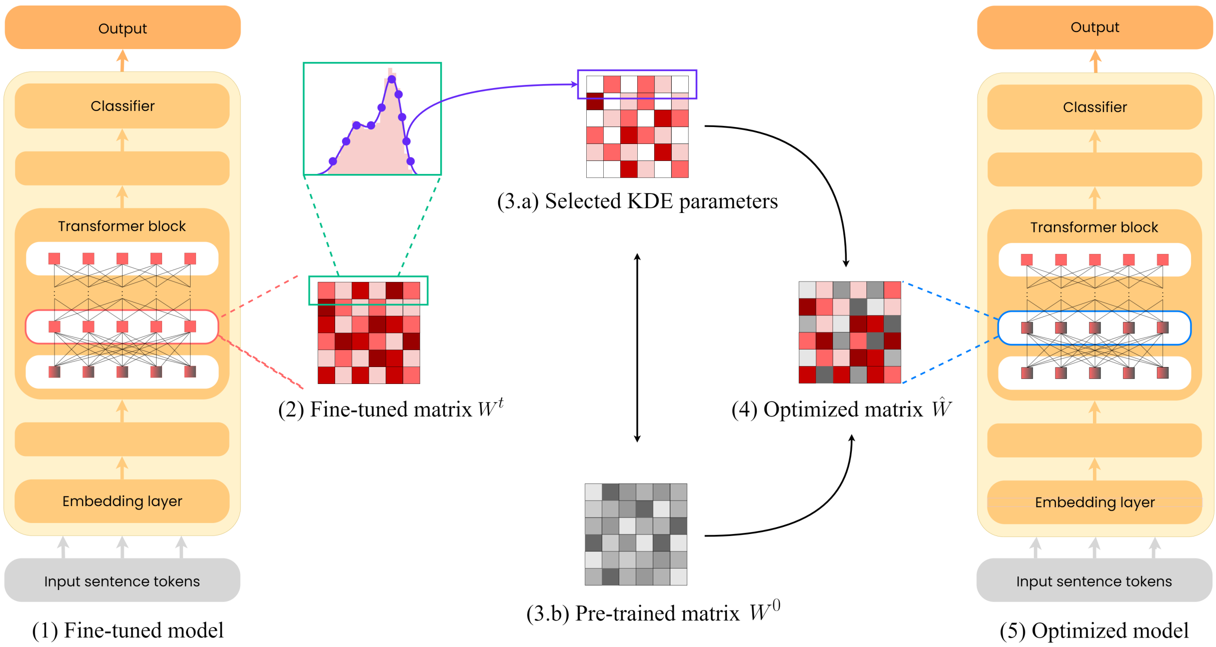


Figure 2: KEN workpath: From a fine-tuned model (1), for each of its fine-tuned matrices (2), the row distribution and the respective KDE (Kernel Density Estimator) are calculated. All values within the KDE are selected (3.a), while the remainder are restored to their pre-tuned value (3.b). The resulting optimized matrix (4) is then fed back into the model (5)

FLOP decomposes each matrix into smaller rank-1 components based on the magnitudes of the matrix entries. Instead, for embedding layers, FLOP adaptively prunes dimensions based on word clusters. This means that FLOP only prunes dimensions that are not frequently used (Joulin et al., 2017; Bastings et al., 2019), which helps to reduce the model size without sacrificing performance.

Block Movement Pruning (BMP: Lagunas et al., 2021) introduces an extension to the movement pruning technique used in transformers (Sanh et al., 2020). This approach reduces the size of each matrix in a transformer model by dividing it into fixed-sized blocks. Regularization is then applied, and the NN is trained through distillation to match the performance of a teacher model. Our focus is on two pruning methods: Hybrid and HybridNT. The key difference between these two approaches is that HybridNT does not involve the use of a teacher model during training (No Teacher).

Low-Rank Adaptation of Large Language Models (LoRA: Hu et al., 2021) is a novel fine-tuning method that leverages low-rank decomposition to reduce the parameter size of LLMs while preserving their performance. This approach involves decomposing LLMs weight matrices into low-rank components, which are then fine-tuned along with the original weights. LoRA enables efficient parameter adaptation to specific tasks without compromising the model generalization capabilities.

4 KEN pruning algorithm

KEN (**K**ernel density **E**stimator for **N**eural network compression) pruning algorithm is designed to identify and extract the most essential subnetwork from transformer models following the main idea of the *winning ticket* hypothesis (Frankle and Carbin, 2018). Our algorithm effectively prunes the network by employing Kernel Density Estimators (KDEs), retaining only the essential parameters and resetting the rest to their pre-trained values. The optimized subnetwork can be stored independently and seamlessly integrated into its pre-trained configuration for downstream applications.

KEN through KDEs, generalizes the point distribution of each transformer matrix, capturing the *smoothed* version of the original fine-tuned model. To prevent the complete deconstruction of the initial matrix composition, KEN applies KDEs to individual rows. The KDE calculation requires a k value, which defines the number of points employed in the distribution calculation which directly influences the number of retained fine-tuned parameters (Fig. 1). Thus, a lower k value indicates a closer resemblance to the pre-trained model while a higher k value reflects a closer alignment with its fine-tuned version.

KEN algorithm operates in three primary steps:

Step 1: Parameter Extraction and KDE Calculation Given a pre-trained matrix W^0 of a layer l:

$$W^0 = \{w^0_{1,1}, ..., w^0_{n,m}\} \quad | \quad W^0 \in \mathbb{R}^{n \times m}$$

and its corresponding fine-tuned counterpart W^t:

$$W^t = \{w^t_{1,1}, ..., w^t_{n,m}\} \quad | \quad W^t \in \mathbb{R}^{n \times m}$$

for each row r^t_i of the fine-tuned matrix W^t:

$$r^t_i = \{w^t_{i,1}, ..., w^t_{i,m}\} \quad \forall i \in [1, n]$$

KEN calculates the KDE distribution of the row r^t_i using a bandwidth parameter h determined following Scott's rule of thumb (Scott, 2015).

$$h = 1.06 \cdot \hat{\sigma} \cdot n^{-\frac{1}{5}}$$

where $\hat{\sigma}$ is the standard deviation of r^t_i.

Step 2: Parameter Retention and Pre-trained Value Reset The k points that best fit the r^t_i row distribution are identified using the KDE likelihood, while the others are reset to their pre-trained values. This process results in an optimized row $\hat{r}_i$:

$$\hat{r}_i = \{\hat{w}_{i,1}, ..., \hat{w}_{i,m}\} \quad \forall i \in [1, n]$$

computed using the following binary function:

$$f(\hat{w}_{i,j}) = \begin{cases} w^t_{i,j} & \text{if} \quad w^t_{i,j} \in \text{ KDE likelihood} \\ w^0_{i,j} & \text{otherwise} \end{cases} \tag{1}$$

Step 3: Matrix Replacement and Optimized Fine-tuned Model After applying the previous step on each row, the optimized matrix $\hat{W}$:

$$\hat{W} = \{\hat{w}_{1,1}, ..., \hat{w}_{n,m}\} \quad | \quad \hat{W} \in \mathbb{R}^{n \times m}$$

will replace the original fine-tuned matrix W^t within the model.

KEN operates iteratively, replacing the W^t matrix with $\hat{W}$ during each iteration. Therefore, after the $t - th$ iteration, the model will have $t - optimized$ matrices, effectively replacing the fine-tuned matrices without creating any additional versions of the model. This versatility allows KEN to prune the entire model or specific layer ranges.

Algorithm 1: Generate the optimized $\hat{W}$ matrix using KEN

Data: $W^0 = \{w^0_{1,1}, ..., w^0_{n,m}\}$,
$W^t = \{w^t_{1,1}, ..., w^t_{n,m}\}, k$
Result: $\hat{W}$
$\hat{W}[n, m] \leftarrow 0$
for *i = 1 to n* **do**
  `best_points` $\leftarrow KDE(r^t_i, k)$
  for *j = 1 to m* **do**
    $\hat{r}^t_i \leftarrow []$
    if $r^t_i[j]$ *in* `best_points` **then**
      $\hat{r}^t_i[j] \leftarrow r^t_i[j]$
    else
      $\hat{r}^t_i[j] \leftarrow r^0_i[j]$
    end
  end
  $\hat{W}[i] \leftarrow \hat{r}^t_i$
end
return $\hat{W}$

Algorithm 1 provides a more formal explanation of the three steps described for generating the optimized matrix $\hat{W}$. Additionally, the graphical representation in Fig. 2 offers a clear and comprehensive visualization of all KEN steps, while Fig. 3 displays different $\hat{W}$ matrices obtained using various k values.

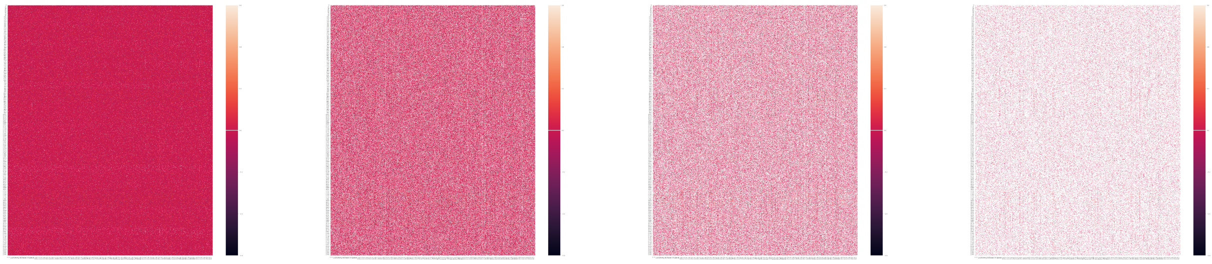
5 Experiments

To validate our algorithm, we conducted a series of extensive case studies. Sec. 5.1 describes the experimental setup, including the models employed and the k values tested. Additionally, Sec. 5.2 focused on investigating the feasibility of saving and loading compressed data.

5.1 Experimental set-up

To evaluate KEN pruning algorithm performance across different architectures and datasets, we conducted a thorough series of experiments using seven distinct transformer models. To maintain consistent evaluation conditions, we uniformly divided each dataset into training, validation and test sets. These divisions remained consistent throughout our experiments and across models. All datasets were imported from Huggingface[2]. To achieve optimal performance, we fine-tuned each model before applying KEN algorithm per each dataset, adjusting

[2] https://huggingface.co/datasets



(a) Fine-tuned matrix (b) Reset params 34.90% (c) Reset params: 60.94% (d) Reset params: 86.98%

Figure 3: Comparing the impact of KEN parameter selection on the same fine-tuned matrix (a). Matrix (a) represents the `in_proj` matrix at layer 0 of a DeBERTa model trained on the `AG_NEWS` dataset. No selected parameters are blank

the number of epochs until the fine-tuned model achieved the best F1-weighted score. Despite what the literature suggests, we used the F1 measure instead of classical accuracy as a comparison metric - if not explicitly used by the comparison benchmarks - because it delivers more reliable predictions, particularly on strongly unbalanced datasets.

To fully assess KEN capabilities, we gradually increased the k value required by the algorithm, starting from a low k value and incrementally increasing it until its fine-tuned version was reached. This incremental approach allowed us to identify the critical *threshold value* whereby the compressed model obtained results similar to its fine-tuned version or when the compression value k leads to a catastrophic decline of performances, as reported in Apx. A.

To provide a comprehensive analysis of KEN, we selected different transformer models with unique architecture, attention mechanisms, training approaches or different versions of the same model. Tab.1 compares the architectures of the models examined, emphasizing the number of layers and the number of parameters of each.

Model		# Layers	# params
BLOOM_{1B7}	(Workshop et al., 2022)	24	1.72 B
BLOOM_{560k}	(Workshop et al., 2022)	24	560 M
DeBERTa	(He et al., 2020)	12	138 M
Bert	(Devlin et al., 2018)	12	109 M
Ernie	(Sun et al., 2020)	12	109 M
DistilBERT	(Sanh et al., 2019)	6	66 M
Electra	(Clark et al., 2020)	12	33 M

Table 1: Properties of the analyzed models

5.2 Model compression

Transformer models, like many neural networks, often have large file sizes. A fine-tuned transformer can range from 500 MB to 2GB or more. However, the KEN algorithm reduces this size by selecting and retaining a subset of k parameters while restoring the rest to their pre-trained values. This process creates a more concentrated model that only includes the essential k values for each matrix, resulting in significant weight reduction. To quantify the effectiveness of KEN, we save the compressed model generated during this phase and compare it to its original, unpruned version. To ensure a fair comparison, we use the same technique to save both the compressed and original fine-tuned models. However, KEN requires a support file, such as a dictionary, to load the k parameters saved into their appropriate positions during the loading process. This is because during loading, the k fine-tuning values must be loaded into a pre-trained model and the support file provides the necessary mapping to ensure proper placement. Sec. 6.2 provides a comprehensive overview of the compression results obtained during this analysis.

6 Results and Discussion

In this section, we present the results obtained for each KEN main goals. Sec. 6.1 discusses the effectiveness of KEN-pruned models compared to their unpruned counterparts, pruning benchmarks and the state-of-the-art PEFT algorithm. Sec. 6.2 focuses on the process of saving and loading the subnetwork extracted by KEN, comparing the reduced file sizes achieved by it with those of the original models. Finally, Sec. 6.3 shows KEN_{viz}, illustrating its applications.

6.1 Experiment results

To evaluate the efficacy of KEN, we conducted a series of experiments across different classification and sentiment analysis datasets. For each dataset, we implemented KEN multiple times, employing

Model	Trainable params	Reset params (%)	AG-NEWS	EMO	IMDB	YELP_POLARITY	glue-sst2
$BLOOM_{1B7}$	442M	74.31	87.5 (±0.1)	**88.0** (±0.1)	76.6 (±0.1)	**96.1** (±0.1)	**80.4** (±0.1)
	531M	69.17	92.2 (±0.1)	**90.6** (±0.1)	84.2 (±0.1)	**96.3** (±0.1)	**90.9** (±0.1)
	664M	61.46	**93.1** (±0.1)	**90.1** (±0.1)	**87.6** (±0.1)	**96.5** (±0.1)	**92.9** (±0.1)
$BLOOM_{560k}$	411M	26.34	91.3 (±0.1)	**81.4** (±0.1)	**82.7** (±0.1)	**95.2** (±0.1)	**92.4** (±0.1)
	420M	24.80	91.8 (±0.1)	**83.0** (±0.1)	**84.3** (±0.1)	**95.3** (±0.1)	**92.1** (±0.1)
	429M	23.26	**92.1** (±0.1)	**84.0** (±0.1)	**85.8** (±0.1)	**95.3** (±0.1)	**92.3** (±0.1)
DeBERTa	92M	33.86	92.2 (±0.1)	**87.9** (±1.2)	82.5 (±5.1)	95.9 (±0.4)	94.6 (±0.2)
	99M	28.35	**92.7** (±0.1)	**87.3** (±1.0)	88.3 (±1.1)	**96.1** (±0.2)	**94.9** (±0.1)
	107M	22.84	**92.9** (±0.1)	**87.1** (±1.2)	**89.8** (±0.1)	**96.2** (±0.1)	**94.8** (±0.1)
Bert	69M	37.05	**93.4** (±0.1)	84.2 (±1.1)	86.8 (±0.1)	**95.0** (±0.4)	**93.7** (±0.5)
	75M	31.80	**93.7** (±0.2)	**87.4** (±0.7)	**87.3** (±0.1)	**95.0** (±0.5)	**93.7** (±0.4)
	80M	26.55	**93.6** (±0.1)	**87.9** (±0.3)	**87.6** (±0.1)	**95.1** (±0.4)	**93.8** (±0.4)
Ernie	69M	37.05	**93.3** (±0.4)	**89.1** (±0.6)	**89.4** (±0.2)	**95.8** (±0.1)	**94.1** (±0.2)
	75M	31.80	**93.3** (±0.3)	**88.7** (±1.2)	**89.2** (±0.2)	**95.8** (±0.3)	**93.8** (±0.2)
	80M	26.55	**93.8** (±0.2)	**88.1** (±0.8)	**89.6** (±0.3)	**95.9** (±0.2)	**93.4** (±0.2)
DistilBERT	44M	34.39	92.3 (±0.6)	**88.1** (±1.4)	83.2 (±1.1)	94.6 (±0.1)	**91.9** (±0.2)
	47M	28.92	**93.1** (±0.2)	**88.8** (±0.6)	84.4 (±0.5)	94.7 (±0.1)	**91.9** (±0.1)
	51M	23.45	**93.3** (±0.2)	**88.2** (±0.3)	**84.6** (±0.9)	**94.9** (±0.1)	**92.0** (±0.1)
Electra	8.9M	75.56	84.1 (±2.4)	84.3 (±0.4)	78.9 (±0.5)	88.5 (±0.9)	79.9 (±0.7)
	12M	64.75	89.7 (±0.3)	**86.0** (±0.3)	82.0 (±0.5)	92.1 (±0.8)	85.0 (±0.2)
	14M	55.94	**91.3** (±0.2)	**85.6** (±0.3)	84.3 (±0.1)	**93.7** (±0.4)	90.1 (±0.1)

Table 2: Results on various datasets obtained using different trainable parameters. Bold results indicate a similar or better F1-weighted value compared to the original (*unpruned*) model. The reset params column indicates the percentage of the restored pre-trained params in the model. Other results are shown in Apx.B

varied k values and calculating the mean and standard deviation of the resulting F1-weighted scores. The complete dataset list can be found in Apx. B. As evidenced in Tab. 2, KEN successfully compressed all analyzed models without sacrificing their original, unpruned performance. We observed a remarkable reduction in overall model parameter count, ranging from a minimum of 25% to a substantial $\approx 70\%$ for certain models. Intriguingly, the models with both the highest and lowest parameter counts exhibited the most significant parameter reduction. Additionally, for each model under examination, we observed no substantial difference in performance as the percentage of reset parameters increased, maintaining a remarkable resemblance to the unpruned model performance. This observation underscores KEN exceptional generalization capability, balancing performance and compression even at middle-high compression rates.

We compared KEN to other pruning algorithms specifically designed for transformer models, including FLOP, Hybrid and HybridNT as described in Sec. 3. It is essential to note that Lagunas et al. (2021) models (Hybrid and HybridNT) only prune the attention layers and not the entire model. To facilitate a comprehensive and standardized comparison of all algorithms, we recalibrated the size of their models based on our holistic perspective, ignoring any partial considerations. We combined the results obtained in their publication with those obtained from KEN and FLOP in Tab. 3. KEN outperformed all other compared models with a significant performance gap while utilizing fewer parameters in every instance. In addition to these findings, we conducted a thorough analysis of FLOP, which is the most complete pruning algorithm studied and, like KEN, decomposes original matrices to derive pruned ones. We conducted additional experiments on all models where FLOP could be applied, using the datasets listed in Tab. 2. We compared the results obtained from FLOP with those of KEN, which employed fewer parameters than FLOP. As shown in Tab. 4, FLOP outperforms KEN in only one instance. For all other models and datasets analyzed, KEN consistently outperforms FLOP.

Model	Trainable params	glue-sst2 Accuracy
Bert-base	109M	93.37
Hybrid	94M	93.23
HybridNT	94M	92.20
KEN	**80M**	**93.80**
Hybrid	66M	91.97
HybridNT	66M	90.71
Sajjad et al. (2020)	66M	90.30
Gordon et al. (2020)	66M	90.80
Flop	66M	83.20
KEN	**63M**	**92.90**

Table 3: Pruning algorithm comparations on SST-2 datasets

Model	Pruning algorithm	Trainable params.	AG-NEWS	EMO	IMDB	YELP_POLARITY	glue-sst2
BLOOM_{1B7}	KEN	531M	**92.2** (±0.1)	**90.6** (±0.1)	**84.2** (±0.1)	**96.3** (±0.1)	**90.9** (±0.1)
	FLOP	1.1B	90.1 (±1.3)	84.0 (±1.9)	80.9 (±0.3)	85.5 (±3.5)	80.7 (±1.7)
BLOOM_{560k}	KEN	404M	**91.3** (±0.1)	**85.5** (±3.5)	**81.3** (±0.3)	**94.8** (±0.5)	**92.0** (±0.4)
	FLOP	408M	91.0 (±0.6)	84.0 (±2.3)	72.1 (±7.1)	87.0 (±0.5)	81.8 (±0.5)
DeBERTa	KEN	84M	**91.4** (±0.6)	**88.9** (±1.5)	**82.5** (±3.1)	**96.0** (±0.2)	**92.8** (±0.4)
	FLOP	88M	90.6 (±0.7)	83.1 (±1.7)	81.1 (±0.8)	91.4 (±0.1)	82.3 (±1.1)
Bert	KEN	57M	**91.6** (±0.7)	**86.0** (±0.5)	**84.9** (±0.8)	**93.8** (±1.6)	**92.8** (±0.5)
	FLOP	66M	90.9 (±0.9)	83.3 (±0.8)	80.5 (±0.6)	90.2 (±0.6)	83.2 (±0.2)
Ernie	KEN	57M	**91.5** (±1.4)	**88.3** (±0.4)	**87.6** (±0.6)	**95.7** (±0.1)	**94.1** (±0.4)
	FLOP	67M	89.8 (±0.4)	83.8 (±2.3)	81.1 (±0.8)	90.9 (±0.1)	83.2 (±0.9)
DistilBERT	KEN	40M	**91.9** (±0.3)	**88.2** (±1.1)	78.1 (±1.4)	**94.1** (±0.1)	**89.2** (±0.7)
	FLOP	45M	90.7 (±0.9)	83.2 (±1.2)	**81.2** (±0.9)	90.7 (±0.1)	82.4 (±1.2)
Electra	KEN	14M	**91.3** (±0.2)	**85.6** (±0.3)	**84.3** (±0.1)	**93.7** (±0.4)	**90.1** (±0.1)
	FLOP	28M	90.9 (±0.3)	83.1 (±2.1)	81.2 (±0.1)	90.5 (±0.1)	81.1 (±0.3)

Table 4: Comparation between KEN and FLOP pruning algorithms on different datasets. Mean and standard deviation are calculated on equal runs for each dataset and algorithm analyzed. The *Trainable params* column indicates the number of parameters used by each algorithm after the pruning phase.

Although KEN belongs to the *winning ticket pruning* algorithms family, it shares similarities with Parameter Efficient Fine-tuning (PEFT) algorithms. This is because both approaches aim to identify a subset of optimal parameters within the fine-tuned model. We thoroughly evaluated KEN and compared it to LoRA, which is currently the state-of-the-art PEFT algorithm. We applied LoRA and KEN to the same layers of each model and then trained the LoRA-based models using five times more training epochs than their KEN-based counterparts. Additionally, we gradually increased the number of rank decomposition matrices for each model from 16 to 768, which is the average size of the matrices in the tested models. In each LoRA-based experiment, only the LoRA-specific parameters were designated as either trainable or not. Our results, presented in Fig. 4, demonstrate that KEN consistently outperforms LoRA in terms of F1-measure while utilizing fewer trained parameters. However, when LoRA parameters are not the only ones trained, KEN and LoRA generally produce similar results. Nevertheless, LoRA consistently requires a larger parameter count than KEN. These compelling results provide strong evidence supporting our hypothesis that strategically selecting a subset of parameters and resetting the remainder offers a promising alternative to conventional pruning techniques.

6.2 Compression values

One of KEN main goals, is to significantly reduce the overall size of transformer models, including their file sizes. To achieve this, KEN leverages a subnetwork comprising only k-trained parameters, allowing it to be saved and then injected into its pre-trained counterpart. This process requires a support file, like a dictionary, that specifies the precise location of each saved parameter within the pre-trained model. To guarantee an unbiased comparison between the original and compressed model sizes, the compressed one is saved using identical techniques and format as the original model. For each transformer analyzed, two compressed versions are generated using both high and low k values.

Model	Total params	Original file size	# trainable params	Compressed file size (Model + support dict)
BLOOM_{1B7}	1.72B	7,055 MB	664M	**3,071 MB** (2,923 + 148)
			442M	**2137 MB** (2,013 + 124)
BLOOM_{560k}	560M	2,294 MB	429M	**2,084 MB** (1,956 + 128)
			386M	**1,842 MB** (1,731 + 111)
BERT	109M	438 MB	80M	**358 MB** (320 + 38)
			57M	**260.2 MB** (228 + 32.2)
DistilBERT	66M	266 MB	51M	**231.4 MB** (203 + 28.4)
			36M	**165 MB** (145 + 20)
DeBERTa	138M	555 MB	107M	**476.3 MB** (428 + 48.3)
			76M	**348.4 MB** (306 + 42.4)
Ernie	109M	438 MB	80M	**356.9 MB** (320 + 36.9)
			57M	**260.3 MB** (228 + 32.3)
Electra	33M	134 MB	14M	**67.01 MB** (59.1 + 7.91)
			9M	**42.58 MB** (35.5 + 7.08)

Table 5: Comparison of the .pt file size between the original and compressed transformer weights

As shown in Tab. 5, both versions of the compressed models demonstrate substantial memory savings, directly proportional to the number of saved parameters. Specifically, transformers saved using a high k value, thus closely mirroring the structure of the unpruned model, conserving $\geq\approx$100 MB per each. This value increases further as the number of trained parameters saved

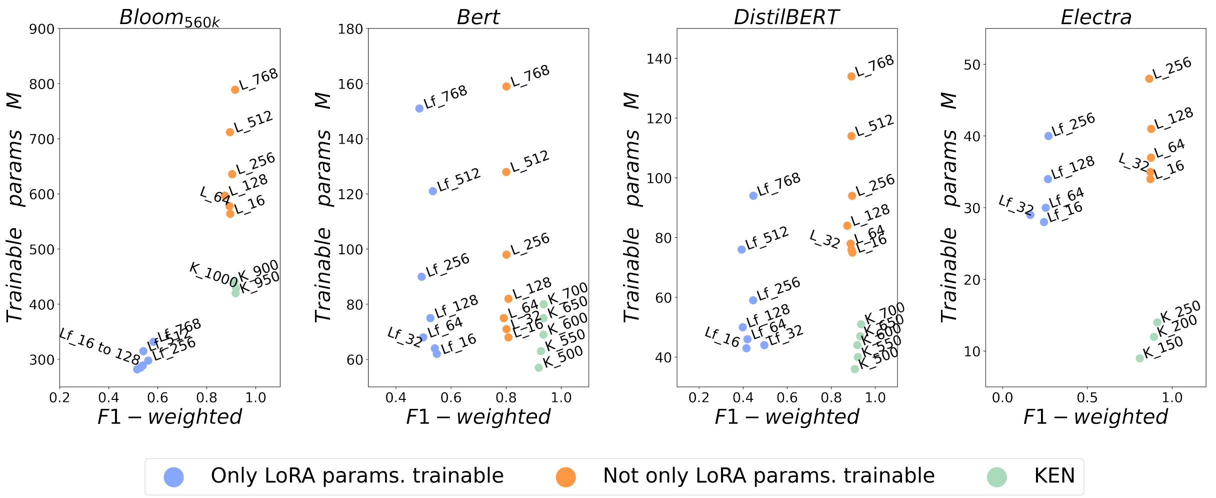


Figure 4: Comparison between KEN and LoRA. Labels for the LoRA marker indicate the dimension of the rank-decomposition matrix analyzed while, for KEN, the k value used

diminishes. The support dictionary for parameter injection, stored using the Lempel-Ziv-Markov chain data compression algorithm, has a negligible impact on the final model weight, which remains significantly smaller than the original. Additionally, the time required to load the injected parameters into the pre-trained model scales linearly with the transformer architecture and the compression employed.

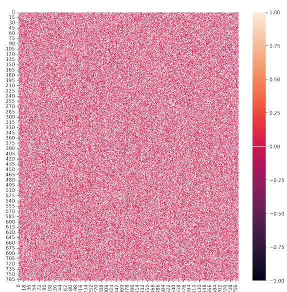
6.3 KEN$_{viz}$

KEN$_{viz}$ is a visualization tool that provides a clear understanding of matrices composition after the application of KEN pruning step. It offers various views to explore the pruned model, including:

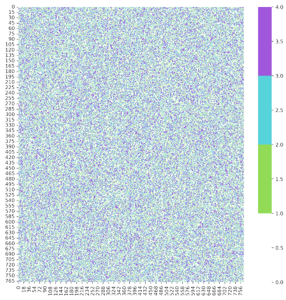
1. **Single Matrix View**: This view offers a clear understanding of the parameters retained by KEN, leaving the pruned elements blank (Fig. 3, Fig. 5a).

2. **Neighbor Count View**: It visualizes the number of non-zero neighbors (horizontally and vertically) for each point in a given matrix. This provides additional information about the remaining parameters and potential parameter clusters that might emerge (Fig. 5b).

3. **Layer-wise View**: This view shows the impact of KEN on the entire model architecture. It iteratively applies the *Single matrix view* to the same matrix on all layers it appears. This allows a layer-by-layer comparison, revealing how the pruning of the same matrix changes in different parts of the network.



(a) Single Matrix View



(b) Neighbor Count View

Figure 5: Output of KEN$_{viz}$ of the key attention matrix at layer 12 of a BERT model trained on `glue-sst2`. Reset parameters 47.92%

The examples in Fig. 5 and Apx. C both indicate that the number of non-zero neighbors for each point remains consistently high even in cases with high reset parameters. This suggests that the chosen parameters not only represent the most effective elements but also display a well-proportioned distribution within each matrix.

7 Conclusions

This paper introduces KEN: a novel non-architecture-specific pruning algorithm that leverages KDE to construct an abstraction of the parameter distribution and selectively retain a finite subset of them while resetting the others to their pre-trained states. Our extensive evaluations on seven different transformer models demonstrate that KEN consistently achieves remarkable compression rates, reducing unnecessary parameters by a minimum of 25% up to ≈ 70% on some models, without compromising model performance. Moreover, by leveraging the KEN core idea, is possible to store only the active subnetwork, leading to substantial memory savings.

We also present KEN$_{viz}$: the KEN visualizer that provides insights into the algorithm operation. KEN$_{viz}$ reveals that KEN uniformly selects parameters across matrices, preventing parameter clusters. With KEN we demonstrate how a simple, non-parametric algorithm commonly used in statistics, can be effectively adopted for model pruning achieving excellent results in both compression and performance.

8 Limitations

One of the major limitations of KEN is its computational efficiency, especially when analyzing large models. Although KEN excels at generating rich distributions with high k values, it faces a trade-off in computational efficiency, particularly for large models. Processing time scales linearly with the model size, number of layers, and chosen k. This primarily impacts the parameter selection stage, not compressed model storage or loading.

Our focus on the sequence classification task ensured consistent results, but unpublished experiments suggest KEN effectiveness extends to other tasks. Future work will explore this broader applicability and investigate potential optimizations for large-scale deployments.

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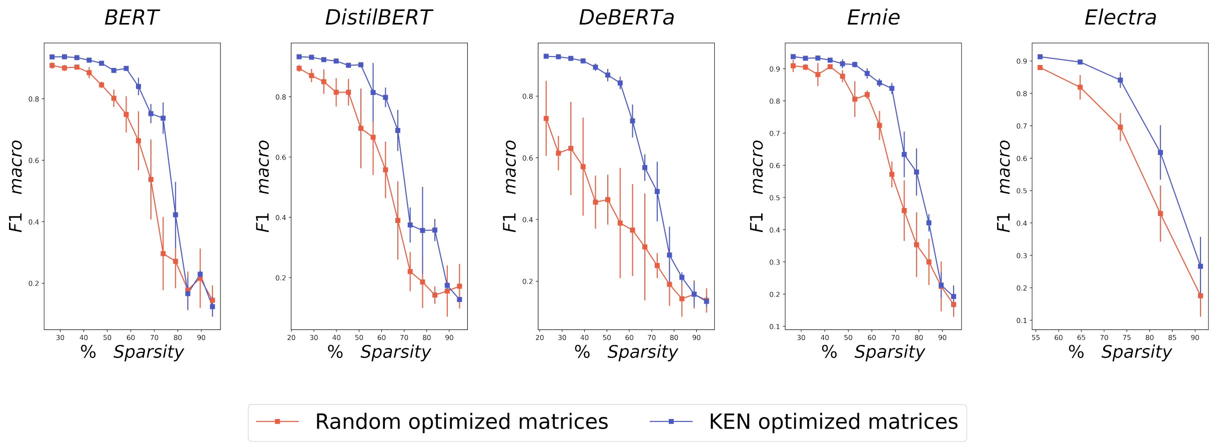


Figure 6: Performance variation on AG-NEWS dataset with different reset parameters percentage value. All the experiments were conducted using KEN *full* configuration

A How to prove the importance of selected parameters

To assess the effectiveness of KEN core idea, which involves selecting parameters based on their distribution using Kernel Density Estimation (KDE), we conducted parallel experiments. In these experiments, we compared KEN against random parameter pruning. Random parameters were either retained or reset to pre-trained values. This enabled us to determine if the selection method used in KEN resulted in a better subnetwork compared to random selection

Formally, for each matrix in a generic model, the optimized matrix $\hat{W}$ contained k randomly selected fine-tuned parameters. Our goal is to determine whether the parameters introduced into a generic transformer model by KEN constituted an optimal subnetwork or if equivalent results could be achieved by randomly selecting the same number of parameters. To address this question, we performed an experiment using the AG-NEWS dataset, comparing the performance differences between extracting $\hat{W}$ matrices using KEN and using k random values for each matrix row.

The results, illustrated in Fig. 6, consistently show that KEN outperforms its random counterpart. KEN achieves a lower error rate and maintains higher performance at reasonable compression levels. However, for all models tested, a compression threshold exists beyond which performance inevitably declines. The KEN algorithm effectively compresses models while minimizing this decline, preserving high performance. Conversely, random parameter selection reaches this threshold earlier, resulting in a larger performance drop and higher error rate. Notably, the best achievable performance with random selection is always lower than or equal to the average achieved with KEN.

Furthermore, when using KEN, the error rate remains minimal within the threshold. This suggests that the subnetwork derived from KEN is not random; rather, it consistently selects the most effective portion of the original network.

Dataset	$BLOOM_{1B7}$	$BLOOM_{560k}$	Bert	DistilBert	DeBERTa	Ernie	Electra
trec	61.46%	23.26%	26.55%	23.45%	22.84%	26.55%	55.94%
rotten_tomatoes	69.17%	24.80%	26.55%	34.39%	44.88%	42.29%	55.94%
hate_speech_offensive	61.46%	23.26%	26.55%	34.39%	22.84%	26.55%	55.94%
hate_speech18	61.46%	23.26%	26.55%	23.45%	33.86%	31.80%	64.75%
scicite	61.46%	23.26%	37.05%	28.92%	22.84%	31.80%	55.94%†
ade_corpus_v2	69.17%	24.80%	52.78%	45.32%	44.88%	63.28%	73.56%
amazon_reviews_multi	69.17%	24.80%	31.80%	34.39%	22.84%	31.80%	55.94%†
poem_sentiment	74.31%	26.34%	58.03%	45.32%	22.84%	47.54%	73.56%
tweet_eval-emoji	74.31%	23.26%	63.28%	23.45%	44.88%	79.02%	55.94%
tweet_eval-hate	61.46%	23.26%	26.55%	61.73%	44.88%	47.54%	55.94%
tweet_eval-irony	61.46%	23.26%	26.55%	23.45%	22.84%	26.55%	64.75%
tweet_eval-offensive	61.46%	23.26%	26.55%†	34.39%	28.35%	31.80%	55.94%
tweet_eval-femminist	61.46%	23.26%	26.55%	39.05%	22.84%	37.05%	64.75%

Table 6: Results obtained from the analysis of additional datasets not shown in Tab.2. The values presented in this table correspond to the lowest percentage of reset parameters that KEN achieved without impacting the model performance. The † symbol denotes a reset parameter rate that falls below the minimum value reported in Tab. 2

B Additional results

This appendix presents additional results obtained using KEN that are not included in Tab. 2.

Tab. 7 provides a comprehensive overview of all datasets analyzed in the paper. In contrast to Tab. 2, Tab. 6 focuses on the specific results included in this appendix. Here, we highlight cases where KEN achieves F1-weighted scores that match or surpass the original unpruned model performance, focusing on the highest percentage of reset parameters for each model on each dataset. This emphasizes KEN remarkable compression capabilities, allowing it to achieve comparable or even improved performance while significantly reducing the model parameter count.

Dataset	Reference
trec	Li and Roth, 2002
AG-NEWS	Gulli, 2005
rotten tomatoes	Pang and Lee, 2005
IMDB	Maas et al., 2011
ade_corpus_v2	Gurulingappa et al., 2012
glue-sst2	Socher et al., 2013
YELP POLARITY	Zhang et al., 2015
hate_speech_offensive	Davidson et al., 2017
hate_speech18	de Gibert et al., 2018
EMO	Chatterjee et al., 2019
scicite	Cohan et al., 2019
amazon_reviews_multi	Keung et al., 2020
poem sentiment	Sheng and Uthus, 2020
tweet_eval-emoji	Barbieri et al., 2020
tweet_eval-hate	Barbieri et al., 2020
tweet_eval-irony	Barbieri et al., 2020
tweet_eval-offensive	Barbieri et al., 2020
tweet_eval-feminist	Barbieri et al., 2020

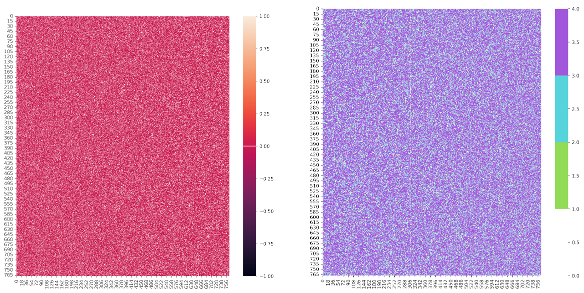
Table 7: Dataset analyzed

C KEN_{viz} examples

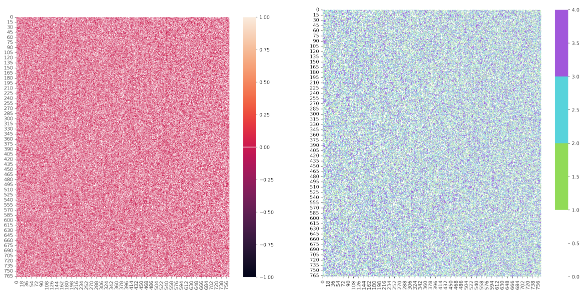
KEN_{viz} generates visual representations of the model pruning after the KEN application. Here, we focus on key matrices from layers 0 and 12 of a BERT model trained on the glue-sst2 dataset (details in Sec. 6.1). For each layer, we present both a single matrix view and a neighbor count view, as described in Sec. 6.3.

BERT was chosen for this experiment due to its exceptional performance across a range of k values during testing (Tab. 2 and Tab. 6). To comprehensively explore how parameter selection patterns evolve, we employed three different k values, representing varying degrees of parameter selection. This allowed us to observe how parameter choices shift as the amount of parameter resetting increases.

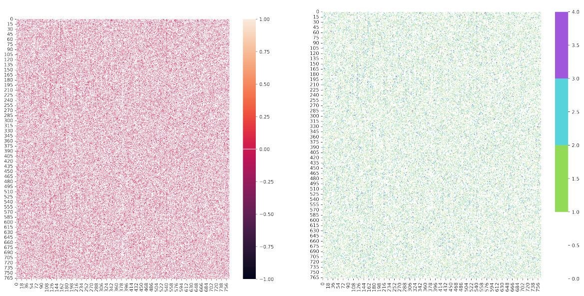
Fig. 7 and Fig. 8 consistently reveal a uniform distribution of parameters within each matrix row across all configurations and layers. This implies an absence of well-defined clusters of selected parameters. Furthermore, the number of neighbors for each parameter remains consistent regardless of the chosen k value.



(a) Parameter reset 21.87%

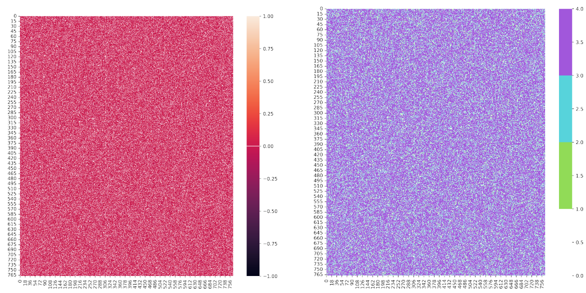


(b) Parameter reset 47.91%

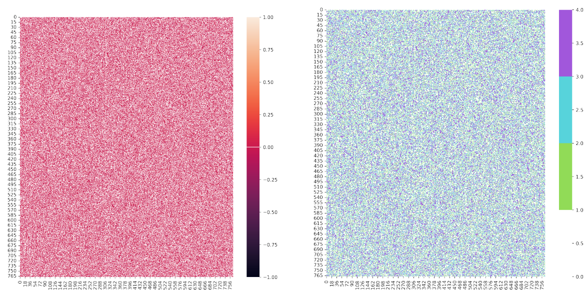


(c) Parameter reset 73.95%

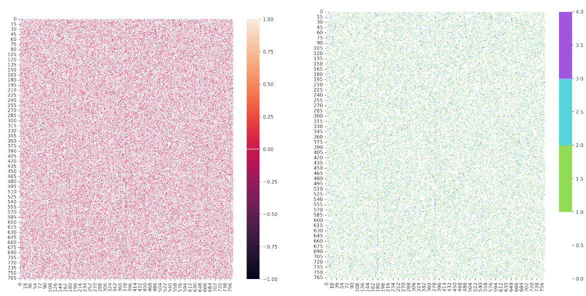
Figure 7: KEN$_{viz}$ visualization of the key attention matrix at layer 0 of a BERT model trained on the `glue-sst2` dataset. The left-hand figures depict the matrix after undergoing the KEN pruning stage, while the right-hand ones showcase the corresponding neighbor counts



(a) Parameter reset 21.87%



(b) Parameter reset 47.91%



(c) Parameter reset 73.95%

Figure 8: KEN$_{viz}$ visualization of the key attention matrix at layer 12 of a BERT model trained on the `glue-sst2` dataset. The left-hand figures depict the matrix after undergoing the KEN pruning stage, while the right-hand ones showcase the corresponding neighbor counts