Efficient Methods for Natural Language Processing: A Survey

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Abstract

Getting the most out of limited resources allows advances in natural language processing (NLP) research and practice while being conservative with resources. Those resources may be data, time, storage, or energy. Recent work in NLP has yielded interesting results from scaling; however, using only scale to improve results means that resource consumption also scales. That relationship motivates research into *efficient* methods that require less resources to achieve similar results. This survey relates and synthesises methods and findings in those efficiencies in NLP, aiming to guide new researchers in the field and inspire the development of new methods.

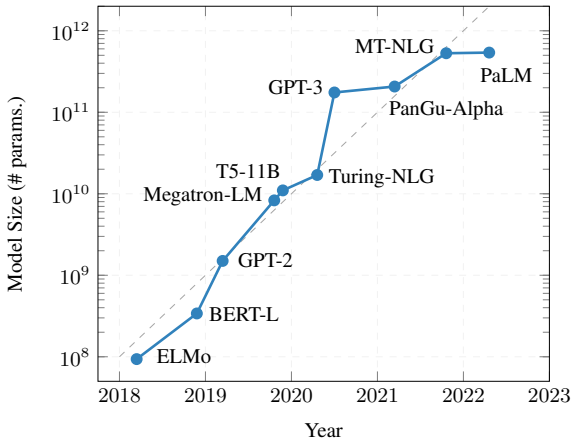

Figure 1: Evolution of the size of large pretrained language models. Adapted from Lakim et al. (2022).

1 Introduction

Training increasingly large deep learning models has become an emerging trend in the past decade (Fig. 1). While the steady increase of model parameters led to state-of-the-art performance and new research directions such as prompting, this also becomes increasingly problematic. First, such models often have restricted access, hence are not democratized, or even if so, still require a substantial amount of compute resources to run (Zhan et al., 2021). Second, they are not sustainable and require large amounts of energy for training and inference (Schwartz et al., 2020a). Third, models cannot be scaled-up indefinitely as their size is limited by the available hardware (Thompson et al., 2020). To tackle these limitations, methods that focus on improving *efficiency* are becoming increasingly popular.

Definition. Efficiency is commonly referred to as the relation between resources going into a system and its output, with an efficient system producing outputs without a waste of resources. For NLP in particular, we consider efficiency as the cost of a model in relation to the results it produces:

$$\text{Cost}(R) \propto E \cdot D \cdot H \tag{1}$$

Equation (1) describes the training cost of an AI model producing a certain (R)esult as proportional to three (non-exhaustive) factors: (1) the cost of model execution on a single (E)xample, (2) the size of the training (D)ataset and (3) the number of training runs required for model selection or (H)yperparameter tuning (Schwartz et al., 2020a). The $\text{Cost}(\cdot)$ can then be measured along multiple dimensions such as the computational, time-wise, or environmental cost. Each of them can be further quantified in multiple ways; for instance, computational cost may include the total number of floating point operations (FLOPs) or the number of model parameters. As using a single cost indicator can be misleading (Dehghani et al., 2021), this survey will collect and organize works on efficient NLP across multiple facets and discuss which dimensions can be beneficial for what use cases and stakeholders.

*Equal contribution.

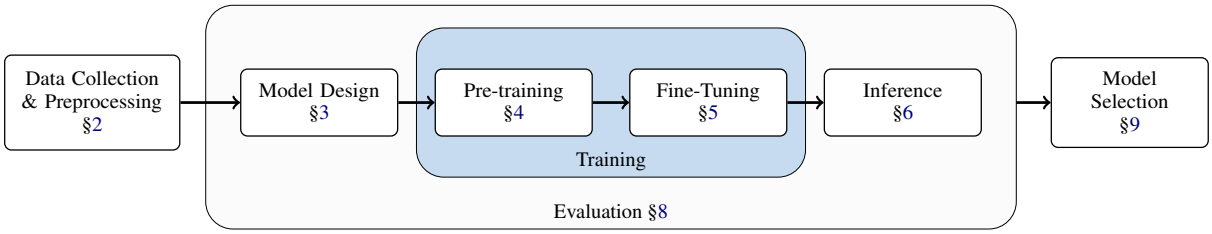

Figure 2: Schematic overview of the efficient NLP stages covered in this paper.

Scope of this survey. Our goal is to provide a gentle introduction into the broad range of methods that aim to improve efficiency with a focus on NLP. We thus structure this survey by following the typical NLP model pipeline (Fig. 2) and present the existing methods that aim to make the respective stage more efficient. To provide a practical guide to efficiency for NLP researchers, we address this work to two groups of readers: (1) Researchers from all fields of NLP working with limited resources. Depending on the bottleneck of resources, readers can directly jump to one of the covered aspects of the NLP pipeline. For instance, if the main limitation is to be expected at inference time, the methods described in Section 6 are the most relevant ones. (2) Researchers interested in improving the state-of-the-art in efficiency methods in NLP. Here, the study can serve as an entry point to find opportunities for new research directions. To guide the reader, we present a diagram with the typology of efficient NLP methods considered in this survey in Fig. 3. Moreover, while hardware choices can have a large impact on the efficiency of models, most NLP researchers do not have direct control over decisions regarding hardware, and most hardware optimizations can be employed swimmingly during all stages of the pipeline. We hence focus our work on algorithmic approaches, but provide appropriate pointers regarding hardware in Section 7. Finally, we further discuss how to quantify efficiency, what factors to consider during evaluation, and how to decide upon the best suited model.

2 Data

One way to increase efficiency can be to use less training instances and/or to better utilize the available ones. In this survey, we focus on approaches that aim to reduce the training data under the assumption that the provided labels are correct.[1]

[1]For erroneous labels we refer to Northcutt et al. (2021); Paullada et al. (2021); Kreutzer et al. (2022); Klie et al. (2022).

2.1 Filtering

Recent works show that improving *data quality* can substantially boost the performance while reducing training costs (in contrast to increasing the *data quantity*). For instance, Mishra and Sachdeva (2020) find that using ∼2% of the SNLI data (Bowman et al., 2015) can achieve comparable performances to using the full data. Lee et al. (2022b) show that removing duplicates during pre-training can already substantially increase training efficiency with equal or even better model performance. Similar trends are found in the development process of recent models such as OPT (Zhang et al., 2022) that include a deduplication step. Finally, various works focus on better understanding how individual instances contribute towards a model's performance (Swayamdipta et al., 2020).

2.2 Curriculum Learning

Curriculum learning aims to increase data efficiency by finding a good ordering of the available training instances (Elman, 1993; Bengio et al., 2009). Similar trends have been observed by Dodge et al. (2020) for transformer models.

Heuristic approaches. Many approaches opt for an easy-instances-first ordering by heuristically estimating the instance difficulty. For transformer architectures, Platanios et al. (2019) find that considering the competence of the model can further improve performance and reduce training time in neural machine translation (NMT). Similar results have been observed in natural language understanding (Xu et al., 2020) and question answering (Tay et al., 2019). For language modeling, Press et al. (2021) show that an initial training on short sequences can substantially reduce training time while retaining model performance. Agrawal et al. (2021) further investigate binning training instances based on their complexity and achieve comparable performances with less training steps.

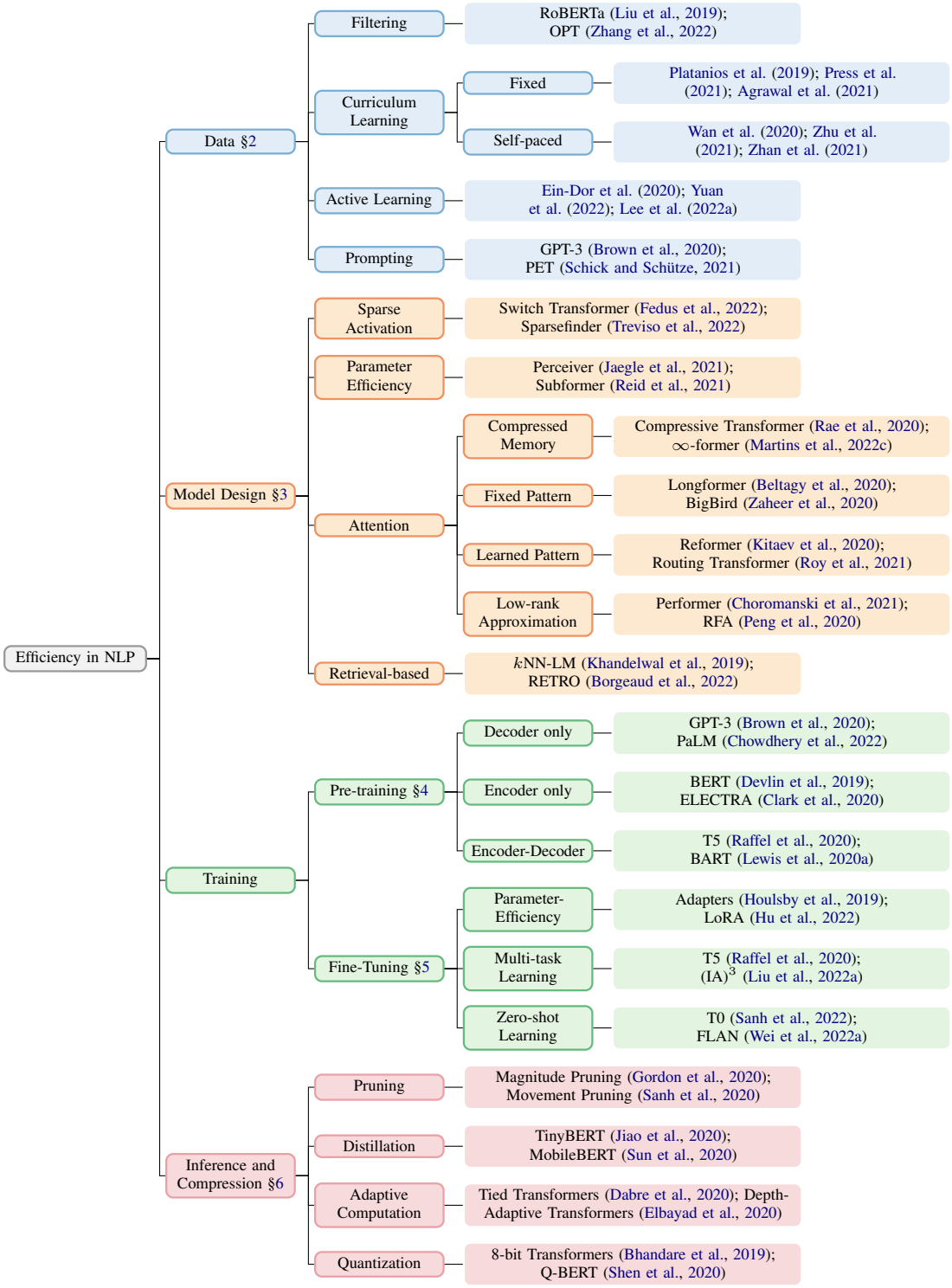

Figure 3: Typology of efficient NLP methods.

Self-paced Learning. Instead of using heuristics such as sentence length or word rarity (Platanios et al., 2019; Zhang et al., 2019; Zhao et al., 2020; Xu et al., 2020), *self-paced learning* adaptively selects instances that would be useful for model training (Kumar et al., 2010). Self-paced learning has been successfully applied in NMT using the model and data uncertainty (Wan et al., 2020; Zhou et al., 2020) and dialog generation coupled with knowledge distillation (Zhu et al., 2021). Zhan et al. (2021) even propose to learn *meta curricula* that would transfer well to other domains.

2.3 Active Learning

Data efficiency can be improved even before training by selectively annotating instances that are most helpful for model training (Settles, 2012; Ren et al., 2021b). The key challenge is to assess the helpfulness without knowing the actual label. Existing approaches thus often use a model's *uncertainty* or the underlying instance *representation* (or both) for sampling. Uncertainty-based approaches assume that instances with the highest uncertainty add the most information once labeled (Lewis and Gale, 1994) and focus on good uncertainty estimates (Tang et al., 2002; Gal et al., 2017; Yuan et al., 2020). Representation-based approaches instead focus on maximizing the diversity of selected instances (Bodó et al., 2011; Sener and Savarese, 2018; Gissin and Shalev-Shwartz, 2019; Kirsch et al., 2019). Although various works show the potential of active learning for NLP (Ein-Dor et al., 2020; Lee et al., 2020; Yuan et al., 2022), there are still open questions about its generalizability to different tasks and models (Lowell et al., 2019). Other issues are outliers in the data that can be harmful for uncertainty-based strategies (Karamcheti et al., 2021) and the potential increase in annotation difficulty and consequently, annotation cost (Settles et al., 2008; Lee et al., 2022a).

2.4 Prompting

Inspired by human interactions with models such as GPT-3 (Brown et al., 2020), prompting refers to asking the model to perform a predictive task by casting it as a textual input (Liu et al., 2021a). The final prediction is then inferred from the output of the language model (Li and Liang, 2021). In general, prompts can be either crafted manually or automatically using fill-in templates or prefix strings for token, span, and sentence-level completion (Petroni et al., 2019; Brown et al., 2020; Shin et al., 2020; Li and Liang, 2021). This makes prompting applicable to more challenging NLP tasks, such as question answering, summarization, and machine translation (Schick and Schütze, 2021). Since no training nor fine-tuning is required, prompting emerges as an efficient alternative for handling NLP tasks in an *unsupervised* fashion.[2]

3 Model Design

An active area of research is in designing more efficient models, either by implementing architectural changes or by attaching new modules that accelerate the workflow of the main model. In this section we will outline current developments made in transformers, e.g., by adapting its architecture or combining it with external resources.

3.1 Sparse Activations

As Derczynski (2020) show, the choice (and implementation) of the activation function can make an order of magnitude difference on the execution time. To accelerate inference by leveraging sparse activations, Fedus et al. (2022) propose the Switch Transformer, which routes computation to dedicated specialists ("experts"). This approach is based on a mixture of experts architecture (Jacobs et al., 1991; Shazeer et al., 2017) and can scale to up to a trillion parameters given enough memory bandwidth, which is often the bottleneck that grows with the number of experts (Rajbhandari et al., 2022). Another example of sparse activations is the adaptively sparse transformer model (Correia et al., 2019), which replaces the (dense) softmax activation in attention heads by (sparse) entmax activations, optimally learning the propensity of sparsity of each head automatically from the data. Building on this, Sparsefinder (Treviso et al., 2022) allows a more efficient attention mechanism for transformers by identifying the sparsity pattern of entmax attention before computing it.

3.2 Parameter Efficiency

Some works investigate reducing the number of parameters; for instance, by sharing weights across layers of the model, such as Universal Transformers (Dehghani et al., 2019) and ALBERT (Lan et al., 2019). Perceiver (Jaegle et al., 2021) suggests a similar approach, but inserts the original input within any inner layer. ALBERT further uses matrix decomposition to reduce the size of the embedding layer, which is one of the largest consumer of model parameters. Finally, Subformer (Reid et al., 2021) investigates ways for weight sharing in Transformers, and shows that sharing only the middle layers of the model works better than the alternatives.

3.3 Attention in Transformers

A limitation of attention mechanisms in transformer models is their quadratic dependency on the sequence length, leading to variants that focus on efficient attention for long-range sequences. Existing strategies include better utilizing already

[2] See the survey of (Liu et al., 2021a) for more information.

processed segments, such as via recurrence to connect multiple segments (Transformer-XL; Dai et al. 2019), learning a network to compress a longer-term memory (Compressive Transformer; Rae et al. 2020), separately modeling global and local attention (Ainslie et al., 2020), and modeling long sequences as a continuous-time signal (∞-former; Martins et al. 2022c). Another line of research seeks to reduce the quadratic bottleneck of self-attention by using fixed attention patterns (Longformer; Beltagy et al. 2020, Sparse Transformer; Child et al. 2019, BigBird; Zaheer et al. 2020), or learning attention sparsity patterns by grouping tokens into buckets or clusters (Reformer; Kitaev et al. 2020, SMYRF; Daras et al. 2020, Routing Transformer; Roy et al. 2021). Some strategies modify the attention mechanism by deriving low-rank approximations to the query-key matrices via a reverse application of the kernel trick that renders linear runtime, as in Linear Transformer (Katharopoulos et al., 2020), Performer (Choromanski et al., 2021), and RFA (Peng et al., 2020).[3] Finally, S4 (Gu et al., 2022) is a recent alternative to transformers that leverages a discretization of state space representations and a parameterization of the state matrix, and achieves strong results for very long inputs.

3.4 Retrieval-Augmented Models

A promising direction in text generation is to combine parametric models with retrieval mechanisms, leading to semi-parametric models (Gu et al., 2018; Lewis et al., 2020b).[4] At inference time, the model retrieves tokens / phrases / sentences from a database, which are then used by the model through interpolation of probability distributions (Khandelwal et al., 2019), gating mechanisms (Yogatama et al., 2021), or attention (Borgeaud et al., 2022). This typically amounts to trading model size with the number of database entries. E.g., RETRO (Borgeaud et al., 2022) matches the performance of GPT-3, Jurassic-1 (Lieber et al., 2021), and Gopher (Rae et al., 2021) despite having 25 times fewer parameters, by retrieving chunks of tokens from a 2 trillion token database.

These models also have good generalization properties: by retrieving from domain-specific databases, models can be applied to domains not seen during training (Khandelwal et al., 2019, 2021), avoiding the need to fine-tune the model for each domain. Having an explicit memory also allows retrieval-augmented models to be adapted "on-the-fly". For instance, Martins et al. (2022b) show that adding corrected examples to a database leads to better translations than fine-tuning while reducing the total translation time. A downside, however, is that retrieval-augmented models are generally slow, since they need to perform retrieval during inference. Several recent works proposed strategies to alleviate this issue, such as pruning the database, having smaller input-dependent databases, reducing the representations dimension, caching information, and reducing the number of retrieval steps (He et al., 2021a; Meng et al., 2022; Wang et al., 2021b; Martins et al., 2022a,b; Alon et al., 2022).

4 Pre-training

Pre-training is a common step in developing NLP models (Peters et al., 2018; Devlin et al., 2019). It typically involves a form of self-supervision of large amounts on textual data, such as prediction of masked words (e.g., BERT) or language modeling (e.g., GPT family of models). The pre-trained models are subsequently fine-tuned for specific tasks (Section 5). In addition to improving performance, the pre-training step can significantly improve efficiency (Peters et al., 2018; Kovaleva et al., 2019). For example, He et al. (2019); Neyshabur et al. (2020) show that pre-training improves convergence speed on downstream tasks. As Fig. 1 shows, the increase in size of these models has been constant for the past several years and has revealed capabilities that only emerge once models become very large (Wei et al., 2022b). However, pre-training these increasingly large models is computationally demanding (Strubell et al., 2019; Schwartz et al., 2020a), leading to the important challenge of reducing their costs.

4.1 Dynamic Masking

The choice of the objective task can determine the success of the pre-trained model when applied on downstream tasks. Self-supervised learning objectives have been a key component for pre-training models on large amounts of unlabeled data. These objectives vary depending on whether the task is modeled using a decoder, an encoder, or both.

Decoder only. The classic objective function for decoder only models, such as GPT (Radford et al.,

[3] See Tay et al. (2020) for a survey on efficient attention.

[4] See the survey by Li et al. (2022) for a comprehensive overview of retrieval-augmented text generation models.

2019; Brown et al., 2020) and PaLM (Chowdhery et al., 2022), is the *causal language modeling* (CLM) objective, which predicts the next word given a prefix using the cross-entropy loss over the whole vocabulary.

Encoder only. A common way for pre-training encoder only models is presented by BERT (Devlin et al., 2019), which uses two objective tasks: (1) The *masked language model* (MLM) task, aiming at filling randomly masked tokens of a textual input, and (2) the *next sentence prediction* (NSP) task, with the goal of predicting whether the two random sentences appear consecutively in the training data. To make better use of the available data, various works have investigated masking strategies that differ from the static masking used in BERT. For instance, Liu et al. (2019) show that dynamically masking tokens during training—i.e., randomly masking 15% of the tokens at each step instead of masking them once before training—can already improve efficiency with a comparable performance. In addition, they show that the NSP objective can be dropped from the pre-training phase in order to get better model performance.

Other works show that masking specific tokens (such as objects or content words; Bitton et al., 2021) or more tokens (Wettig et al., 2022) leads to higher performance and more efficient use of the available data. ELECTRA (Clark et al., 2020) and DeBERTa (He et al., 2021b) experiment with *replaced token detection* (RTD), a new self-supervised learning objective that uses a small generator model to replace tokens in the input. Both works show that RTD leads to faster and better performing pre-training compared to BERT.

Encoder-Decoder Another approach, suggested in T5 (Raffel et al., 2020) and BART (Lewis et al., 2020a), uses a denoising *sequence-to-sequence* objective to pretrain an encoder-decoder LM, allowing the decoder to predict a span of tokens for masked positions rather than a single token.

5 Fine-Tuning

Fine-tuning refers to the step of adapting a pre-trained model to a new downstream task. In general, fine-tuning specifically refers to gradient-based training on downstream task data. In this survey, we use a broader definition of fine-tuning that includes any method used to apply a pre-trained model to a downstream task.

5.1 Parameter-Efficient Fine-Tuning

Gradient-based fine-tuning typically involves training all of a model's parameters on downstream task data. This means that each time a pre-trained model is fine-tuned on a new task, an entirely new set of model parameters is created. If a model is fine-tuned on many tasks, the storage requirements can become onerous. The seminal ELMo work originally adapted a pre-trained model to downstream tasks by training a new classification layer and leaving the rest of the parameters fixed. This approach updates dramatically fewer parameters than training the full model but has been shown to produce worse performance and has therefore become less common (Devlin et al., 2019).

An alternative is *parameter-efficient fine-tuning* (PEFT), which aims to adapt a model to a new task while only updating or adding a relatively small number of parameters. Adapters (Houlsby et al., 2019; Bapna and Firat, 2019; Rebuffi et al., 2017), which inject new trainable dense layers into a pre-trained model, were the first PEFT method proposed for NLP models. Adapters have recently been improved by the "Compacter" method of (Karimi Mahabadi et al., 2021), which constructs the adapter parameter matrices through Kronecker products of low-rank matrices. As an alternative to adding new layers, parameter-efficiency can be achieved by directly modifying activations with learned vectors, either by concatenation (Lester et al., 2021; Li and Liang, 2021), multiplication (Liu et al., 2022a), or addition (Ben Zaken et al., 2022). Alternatively, rather than adding new parameters or changing the model's computational graph, it is possible to make updates to the original model cheaper to store through the use of sparse (Sung et al., 2021; Guo et al., 2021) or low-rank (Hu et al., 2022) updates. Finally, it has been shown that optimization can be performed in a low-dimensional subspace (Li et al., 2018); storing the updates in this subspace can be seen as a PEFT method (Aghajanyan et al., 2021b). State-of-the-art PEFT methods add or update roughly four orders of magnitude fewer parameters than full-model fine-tuning without sacrificing (and in some cases improving) performance (Hu et al., 2022; Karimi Mahabadi et al., 2021; Liu et al., 2022a).

5.2 Multi-Task and Zero-Shot Learning

While traditional transfer learning includes fine-tuning, there are other paradigms that allow for

immediate application of a pre-trained model to a downstream task of interest. *Multi-task learning* (Caruana, 1997; Ruder, 2017) aims to train a single model that can perform a wide variety of tasks out of the box. Typically, this is done by explicitly training the model on data from all tasks of interest. If a multi-task model has already been trained on a given downstream task, then no fine-tuning is necessary. Recent work has additionally demonstrated that multi-task models are also amenable to fine-tuning (Raffel et al., 2020; Aghajanyan et al., 2021a; Aribandi et al., 2022; Liu et al., 2022a).

In certain cases, a multi-task model can be applied to a new task without any fine-tuning. This ability is referred to as *zero-shot generalization*. Radford et al. (2017, 2019) and Brown et al. (2020) demonstrated that language models trained with an unsupervised objective were able to perform a variety of tasks out-of-the-box. Later, Sanh et al. (2022) and Wei et al. (2022a) showed that multitask training can also enable zero-shot generalization abilities. While zero-shot generalization can circumvent fine-tuning completely, it has (as of writing) only been demonstrated on large and computationally-intensive models.

6 Inference and Compression

Various approaches have been proposed to improve efficiency at inference time. *Compression* methods such as *pruning* (LeCun et al., 1989) and *distillation* (Hinton et al., 2015) assume that smaller models are more efficient than larger models. *Adaptive computation* works accelerate inference by ignoring inner modules for making a prediction (Schwartz et al., 2020b). Finally, *quantization* is an orthogonal approach that directly increases efficiency by modifying the underlying data type.

6.1 Pruning

Initially proposed by LeCun et al. (1989), removing unnecessary weights from a neural network aims to avoid unnecessary computation to reduce inference time with limited accuracy loss, and furthermore, decrease memory capacity and bandwidth requirements. Pruning can be applied on different levels within a model: for instance, Voita et al. (2019); Michel et al. (2019) find that only few attention heads substantially contribute towards a model's prediction and propose to prune the rest; Correia et al. (2019); Ji et al. (2021); Qu et al. (2022) verified that the weak attention values in the transformers can be pruned without accuracy loss. Others focus on pruning individual weights (Sanh et al., 2019; Gordon et al., 2020) or layers (Dong et al., 2017; Sajjad et al., 2020). Finally, some works try to identify good criteria for pruning specific weights/layers (Sanh et al., 2020; Hoefler et al., 2021) or even propose to dynamically drop layers (Fan et al., 2020) during inference; sometimes in combination with other efficiency methods such as adapters (Rücklé et al., 2021). The increasing popularity of pruning methods has further raised the question of how to quantify and compare them (Tessera et al., 2021; Blalock et al., 2020; Gale et al., 2019).[5]

6.2 Distillation

Whereas pruning primarily focuses on removing weights from a pre-trained model, Hinton et al. (2015) instead propose to train a smaller model (student) from scratch by using the pre-trained model to obtain a supervision signal (teacher). While early works focus on distilling task-specific models (Kim and Rush, 2016), recent works focus on distilling pre-trained models that can then be fine-tuned on specific downstream tasks (Sanh et al., 2019; Liu et al., 2020; Jiao et al., 2020; Sun et al., 2020).

6.3 Adaptive Computation

An alternative to compression approaches can be to adaptively decide for each instance which part of a model to use. For example, *early exit predictions* allow a system to only utilize the outputs of lower (early) layers in a model to make a prediction (Dabre et al., 2020; Elbayad et al., 2020; Schwartz et al., 2020b; Xin et al., 2020).

6.4 Quantization

Various data types can be utilized as the underlying representation in neural networks (Section 7). Mapping high-precision data types to low-precision ones is commonly referred to as *quantization*. While quantization saves memory and computational cost, reducing the precision can lead to a loss in terms of accuracy. Therefore, quantization often requires a careful model construction and training.

Low- and mixed-precision. Various works target specific precision-levels such as integers (Kim et al., 2021), 8-bit (Quinn and Ballesteros, 2018; Zafrir et al., 2019; Bhandare et al., 2019; Prato

[5] A detailed taxonomy of different pruning approaches is introduced by Hoefler et al. (2021).

et al., 2020) and 3-bit quantization (Ji et al., 2021; Zadeh et al., 2022), and even ternary and binary representations (Zhang et al., 2020; Bai et al., 2020). Other works investigate mixed-precision quantization as different components may have a different sensitivity regarding their underlying precision. For instance, Shen et al. (2020) show that embedding layers require more precise parameter representations than the attention layer while Kim et al. (2021) show that nonlinear functions require more bits than the general matrix multiplication. Others define quantization as a constrained optimization problem to automatically identify layers where a lower precision is sufficient (Hubara et al., 2021). These works show that customized quantization schemes across different components can maintain the accuracy while increasing efficiency.

Quantization-aware training. Finally, several works propose to consider quantization already during training to make them robust against performance losses after quantization (Zafrir et al., 2019; Kim et al., 2021; Stock et al., 2021). For instance, Bai et al. (2020); Zhang et al. (2020) propose to utilize knowledge distillation to maintain the accuracy of binarized and ternarized models.

6.5 Other Methods

Although this survey presents the most prominent research areas that aim to improve inference efficiency, there exist several other methods with the same goal. For instance, Wu et al. (2022) combine several methods to achieve utmost model compression, while other works improve task-specific mechanisms, such as beam-search in machine translation (Peters and Martins, 2021). Moreover, parallelism can also be exploited to further increase inference efficiency (Rajbhandari et al., 2022).

7 Hardware Utilization

Finally, we discuss several methods that consider the underlying hardware used for training and inference. A majority of the effort is dedicated to reducing GPU memory consumption as one of the major bottlenecks in transformer models. Note that many of the presented techniques can be applied across different stages of training and inference (Fig. 2), and can be combined for further efficiency.

Data types. Traditionally, neural networks use the IEEE 765 single-precision 32-bit float which consists of 4 bytes representing a floating point number (`float32`). However, this substantially affects the memory consumption in GPUs with the increase of model parameters. Combining half-precision (`float16`) and single-precision (`float32`) data representations can cut a network's memory consumption in half for inference and almost half for training (Micikevicius et al., 2018). An alternative to `float16` is the Brain Floating Point (`bfloat16`) that is utilized in TPUs and can lead to a more stable training (Kalamkar et al., 2019). `bfloat16` and `float16` can furthermore lead to double the FLOP/S due to hardware support in many modern CPUs and GPUs.

Reducing optimizer memory. Because the Adam optimizer keeps track of first and second order momentum, it needs to store two floats for each parameter in the neural network. Therefore, to train a model containing K parameters, the GPU must store $3K$ parameters corresponding to the model, the first and the second order momentum. Libraries like DeepSpeed (Ren et al., 2021a) allows the optimizer to be offloaded from GPU memory and into CPU RAM where the computations are performed in the CPU using highly-efficient AVX instructions. `bitsandbytes` (Dettmers et al., 2022) uses dynamic block-wise quantization and 8-bit integers to represent optimizers. Block-wise quantization requires `bitsandbytes` to split each tensor into blocks that are individually quantized, reducing the inter-GPU communication. `bitsandbytes` can reduce Adam's GPU memory consumption by 75% and, in many cases, speed up training by reducing inter-GPU communication. While `bitsandbytes` runs on GPUs, the method is theoretically compatible with the optimizer offloading presented in DeepSpeed.

Specialized hardware. Specialized hardware for NLP applications that utilizes Application Specific Integrated Circuits (ASICs) or Field Programmable Gate Arrays (FPGAs) exists, but is not broadly available. These hardware designs use dedicated computational units for irregular methods that improve efficiency (such as quantization and pruning discussed in Section 6), hence they improve the efficiency. For example, Zadeh et al. (2020, 2022); Li et al. (2021); Qu et al. (2022) managed to support ultra-low-bit and mixed precision computation that cannot be done on CPUs/GPUs; Ham et al. (2020, 2021); Qu et al. (2022); Wang et al. (2021a) proposed hardware that predicts the

unnecessary components in the transformers and prunes them, including redundant heads/tokens and weak attention values. Qu et al. (2022) specifically proposed specialized hardware to schedule data loading to alleviate the imbalance introduced by pruning. Other works develop new types of dedicated processors and memories to match the properties of the components in the transformers; for instance, softmax and layer normalization (Lu et al., 2020; Liu et al., 2021b), and embedded Resistive RAM (a nonvolatile memory with low latency and energy comsumption) to store word embeddings (Tambe et al., 2021).

Co-design. Finally, we provide some pointers for works that jointly optimize the design of hardware, software, and algorithms which historically has been an important driver of efficiency gains (Hooker, 2021). For instance, Lepikhin et al. (2021) demonstrate that improving the underlying compiler can already substantially improve parallelization allowing them to scale their model up to 600B parameters. Other prominent examples for co-design also focus on improvements of mixture of experts models that consider the underlying hardware leading to substantial speedups (He et al., 2022; Rajbhandari et al., 2022). Lastly, Barham et al. (2022) propose a novel gang-scheduling approach together with parallel asynchronous dispatch that further leads to substantial efficiency improvements.

7.1 Edge Devices

Running advanced NLP models to resource-constrained devices provides better user experience as it preserves user-privacy and reduces inference latency. Various works specifically target increasing the efficiency for on-device settings. SqueezeBERT (Iandola et al., 2020) is a mobile BERT-like architecture that incorporates efficient group convolutions into self-attention and it runs faster on mobile devices than other efficient models like MobileBERT (Sun et al., 2020). EdgeFormer (Ge and Wei, 2022) is a lightweight encoder-decoder transformer architecture that is designed for on-device settings. It runs on mobile CPUs under low latency and provides high-quality machine translation and grammar error correction abilities. GhostBERT (Huang et al., 2021) uses ghost modules that are built on top of depthwise separable convolutions used in MobileNets (Howard et al., 2017). LiteTransformer (Wu* et al., 2020) utilizes long-short range attention to encode local context by convolutions and captures long range dependencies by attention operations. It improves the Transformer performance on machine translation tasks by a large margin under resource-constrained settings. Finally, ProFormer (Sankar et al., 2021) uses locality sensitive hashing and local projection attention layers to build word embeddings for text classification and reduces the runtime and memory for on-device deployments.

8 Evaluation

To evaluate efficiency, it is important to establish what resource—e.g., money, data, memory, time, power consumption, carbon emissions, etc—one attempts to constrain. Furthermore, efficiency does not intrinsically guarantee a reduction in overall resource consumption, as the resulting cost reduction may lead to an increase in demand and counteract its gains. This is known as Jevons paradox (Jevons, 1866) and is in part moderated by time lag between efficiency gains and demand increase, and external, human-influenced factors such as energy pricing and regulation.

8.1 Measuring Efficiency

There are often multiple factors that need to be traded-off against each other when improving efficiency. For instance, while a longer training of models may increase their task performance, at the same time, it increases the resource consumption.

Pareto optimality. One solution for this issue can be to identify Pareto-optimal solutions, those for which no other system reaches a better or equal task performance with lower resource consumption. As there still may be more than one Pareto-optimal solution, the final choice depends on the application context; e.g., a small, average-quality model and a large, high-quality model can both be optimal. Consequently, as long as a model contributes to or extends the Pareto-optimal curve for a given problem and measurement space, it contributes something new—even if other solutions may use less resources or produce higher quality scores. Advancing NLP through pushing Pareto barriers is an established practice. For instance, the WNGT 2020 machine translation shared task (Birch et al., 2020) considers the Pareto frontier between real time taken, system or GPU memory usage, and model size, as well as BLEU. Especially in MT evaluation, such trade-offs are commonplace (Kim

et al., 2019; Bogoychev et al., 2020; Behnke and Heafield, 2021). Puvis de Chavannes et al. (2021) include power consumption as a trade-off against perplexity to explore Pareto-efficient hyperparameter combinations for transformer models. Finally, Liu et al. (2022b) examine Pareto efficiency for a number of tasks in an attempt to narrow model selection search space to efficient examples.

Power consumption. One resource to measure efficiency is power consumption. There exist various way to measure power consumption, for instance, by using specific hardware such as an electricity meter. While this can provide precise figures with a high temporal accuracy, it cannot provide a fine-grained estimate. Moreover, this does not cover external energy costs such as cooling or networking. Another way is to utilize software tools such as MLCO2 (Luccioni et al., 2019). Some tools even provide a real-time breakdown of the power consumption of different components within a machine (Henderson et al., 2020) or local machine API-reported figures to stop training early if prudent (Anthony et al., 2020). Finally, Hershcovich et al. (2022) introduce a model card for NLP systems that encourages researchers to document efficiency in a consistent manner. Note that measuring power consumption programmatically comes with a number of caveats. First, sampling frequency is often restricted for a number of reasons at various levels of the stack and may result in a lag in measurement start. Consequently, shorter experiments may log an energy use of zero, and there will almost always be some part of a process' real energy demand that is missed. Second, inefficiencies such as heat loss are not reported by current APIs and hence, does not cover cooling and other system management activities. Third, not all architectures and operating systems are supported. For instance, power consumption under OSX is difficult to manage, and direct figures for TPU power consumption are not available.

Carbon emission. Besides power consumption, the aforementioned works often also report the carbon emissions. They are computed using the power consumption and the carbon intensity of the marginal energy generation that is used to run the program. Thus, low-energy does not mean low-carbon, and high-energy models can—in the right region and with some care—be zero-carbon in terms of point energy consumption impact, if executed at the right time (i.e., when the energy mix is low-carbon intensity). For estimating the CO2 emissions from a specific program execution, APIs such as ElectricityMap[6] provide real-time access to carbon intensity for many regions. However, as carbon intensity varies and is affected by other factors like the power usage efficiency in a data center, it is often a poor basis for comparison; in fact, Henderson et al. (2020) recommend to use multiple runs for a stable estimate. Furthermore, one needs to consider that zero-carbon program executions still consume energy (to beware of Jevons paradox).

Financial impact. Monetary cost is a resource that one typically prefers to be efficient with. Both fixed and running costs affect NLP, depending on how one chooses to execute a model. As hardware configurations and their prices form discrete points on a typically non-linear scale, it is worth paying attention to efficient cost points and fitting to these. Implementing pre-emptible processes that can recover from interruptions also often allows access to much cheaper resources. When calculating or amortizing hardware costs, one should also factor in downtime, maintenance, and configuration. Measuring the total cost of ownership (TCO) provides a more useful metric.

FLOP/s. Finally, a frequently reported efficiency measure are the floating point operations (FLOPs) and floating points per second (FLOP/s). While this discrete metric sounds well-defined in terms of what the hardware does, there is some variation at multiple stages of the stack, adding uncertainty. For example, different operations may count as a FLOP on different hardware; non-floating-point operations are not considered; hardware is rarely 100% utilised and achieving this productively is a challenge, so theoretical FLOP/s performance cannot be multiplied with time elapsed to yield the amount of computing performed. Still, FLOP/s per unit power can indicate which hardware choices have the potential to offer Pareto-efficient trade-offs for these factors (Hsu et al., 2005).

8.2 Trade-offs with other Desiderata

One major, but seldomly studied concern when improving the efficiency are trade-offs with other desiderata such as fairness and robustness. For instance, Hooker et al. (2020); Renduchintala et al. (2021); Silva et al. (2021) find that compression

[6] https://electricitymap.org

techniques such as pruning can amplify existing biases; Mohammadshahi et al. (2022) further showcase this in a multilingual setting. So far, not many works investigate preserving a model's fairness when increasing its efficiency. To quantify such effects, Xu et al. (2021) propose loyalty as a novel metric. Finally, Xu and Hu (2022) attempt to study these effects more systematically, however, with mixed conclusions. While, more positive insights have been found with other desiderata such as the out-of-distribution (OOD) generalization (Ahia et al., 2021; Iofinova et al., 2022) and model transfer (Gordon et al., 2020), we find that more work is necessary to better understand the impact of efficiency methods on them.

8.3 Open Challenges in Measuring Efficiency

The choice of hardware can lead to pronounced differences in certain efficiency measurements such as latency and thoroughput (Lee-Thorp et al., 2022). Properly measuring efficiency still remains a big challenge. For instance, Cao et al. (2020) show that using software-based tools can often introduce large errors in estimating the true energy. Instead, more accurate estimates may be obtained by training a classifier on ground-truth energies obtained from power monitors (Cao et al., 2021); however, scaling them to new hardware devices and multiple GPUs stull remains an open problem.

Separating different stages. It is important to separately characterize the efficiency of pretraining and fine-tuning stages. For example, models may present different memory requirements during training yet result in trained models with comparable inference memory consumption. This is because training often involves design choice that increases the memory overhead of backward propagation. For example, certain optimizers can require significantly more memory. In a similar vein, parameter sharing techniques have few benefits during training but show memory improvements at inference (Dehghani et al., 2021).

Disagreement between cost factors. As partially discussed in Section 7, cost indicators may disagree with each other. For instance, mixture of experts increase the overall parameter count, but improve the trade-off between quality and FLOPs, as they minimize the per-data cost by routing to subsections of the model (Rajbhandari et al., 2022). Conversely, unstructured sparsity techniques can significantly minimize the overall number of FLOPs. Yet in practice, it introduces low-level operations that can lead to far higher memory requirements to store the indices that indicate what part of the matrix is sparse (Qu et al., 2022). Finally, Dao et al. (2021) find specific sparsity patterns that achieve more predictable speedups with current hardware.

9 Model Selection

Hyperparameter search. The performance of machine learning methods can be substantially improved by a careful choice of hyperparameters. Model-based techniques such as Bayesian optimization (BO) (Snoek et al., 2012; Feurer et al., 2015) and graph-based semi-supervised learning (Zhang and Duh, 2020) use surrogate models to search efficiently for optimal hyperparameters, avoiding expensive grid search or manual tuning. The SMAC3 library (Lindauer et al., 2022) implements several BO strategies, including a budget-limited variant for expensive deep learning tasks, and is integrated into *auto-sklearn* (Feurer et al., 2020) and *auto-pytorch* (Zimmer et al., 2021).

A complementary approach to reduce the cost of hyperparameter optimization is the successive halving algorithm (SHA) (Jamieson and Talwalkar, 2016) and its massively parallel variant, asynchronous SHA (ASHA, Li et al. 2020), which test multiple hyperparameter settings in parallel for a fixed number of training iterations, then discard the half of the settings with the worst validation set performance. However, with limited computational budgets, both BO and ASHA can sometimes fail to identify good settings (Liu and Wang, 2021). It is unclear whether these methods can also be used to choose random initial weights or to order training samples, which also have a substantial effect on model performance (Dodge et al., 2020).

Hyperparameter transfer. To minimise the number of trials needed to find optimal hyperparameter settings, we can transfer knowledge from other datasets or tasks – similar to how an ML engineer might select reasonable settings by hand. Transfer neural processes (Wei et al., 2021) provide a way to transfer observations, parameters and configurations from previous tasks using Bayesian optimization with a neural process as the surrogate model. This can lead to more accurate models with fewer trials than conventional BO approaches, but has yet to be tested for large NLP models. Furthermore, when training a large neural network,

the cost of each tuning step can be reduced using μTransfer (Yang et al., 2021) to tune a small model, then transfer the hyperparameters to a larger model. First, the target model is parameterized using Maximal Update Parametrization (μP) (Yang and Littwin, 2021), which finds a suitable smaller model (reduced width or depth) whose optimal hyperparameters will be similar to those of the larger target model. The small model is tuned using any preferred approach, and the chosen hyperparameter values are then used directly for the large target model. μTransfer is applicable to many different hyperparameters, including learning rate, momentum, weight initialization variance and weight multipliers, but not to those controlling regularization, such as dropout.

10 Conclusion

In this survey, we organized the existing literature according to the traditional NLP pipeline, and provided a broad overview of existing methods to increase efficiency and their shortcomings. As our discussion shows, efficiency in NLP can be achieved in many different ways; but is also subject to various open challenges such as a good metric to quantify it.

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