Multi-armed bandits for online optimization of language model pre-training: the use case of dynamic masking

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Abstract

Transformer-based language models (TLMs) provide state-of-the-art performance in many modern natural language processing applications. TLM training is conducted in two phases. First, the model is pre-trained over large volumes of text to minimize a generic objective function, such as the Masked Language Model (MLM). Second, the model is fine-tuned in specific downstream tasks. Pre-training requires large volumes of data and high computational resources, while introducing many still unresolved design choices. For instance, selecting hyperparameters for language model pre-training is often carried out based on heuristics or grid-based searches. In this work, we propose a novel multi-armed bandit-based online optimization framework for the sequential selection of pre-training hyperparameters to optimize language model performance. We pose the pre-training procedure as a sequential decision-making task, where at each pre-training step, an agent must determine what hyperparameters to use towards optimizing the pre-training objective. Specifically, we propose a Thompson sampling bandit algorithm, based on a surrogate Gaussian process reward model of the MLM pre-training objective, for its sequential minimization. We empirically show how the proposed Gaussian process based Thompson sampling pre-trains robust and well-performing language models. Namely, by sequentially selecting masking hyperparameters of the language model, we achieve satisfactory performance in less epochs, not only in terms of the pre-training MLM objective, but in diverse downstream fine-tuning tasks. The proposed bandit-based technique provides an automated hyperparameter selection method for pre-training Transformer-based language models of interest to practitioners. In addition, our results indicate that, instead of MLM pre-training with fixed masking probabilities, sequentially adapting the masking hyperparameters improves both pre-training loss and downstream task metrics.

1 Introduction

In the field of Natural Language Processing (NLP), models for learning unsupervised representations from unlabeled text based on Transformer architectures \cite{vaswani2017attention} have attained state-of-the-art results on diverse tasks; e.g., question answering and language inference \cite{shoelle2021emerging}. Transformer-based language models (TLMs), such as BERT \cite{devlin2018bert} and RoBERTa \cite{liu2019roberta}, rely on the combination of unsupervised pre-training of the model, and a subsequent task-specific fine-tuning procedure, via additional neural network layers targeted to the task of interest. TLMs are pre-trained over large unlabeled text data using self-supervision, i.e., by learning the relationships between different sections, sentences or words of the input data. Once the TLM is pre-trained over large volumes of text, it can be used in various downstream tasks after fine-tuning task-specific layers.
The key insight from pre-trained TLMs is that they learn language representations or embeddings that are useful across downstream tasks, minimizing the need to retrain the entire model from scratch. The advantage is that extensive pre-training of TLMs can lead to significant downstream performance improvements, i.e., it is worth learning complex TLMs in huge natural language corpora before fine-tuning them for particular tasks.

Following the success of TLMs in general NLP tasks, many have replicated the pre-train, then fine-tune framework in different specific domains, ranging from language models pre-trained with scientific documents in SciBERT (5) and biomedical corpora in BioBERT (32), ClinicalBERT (3), and BlueBERT (17); to in-house, industry-specific implementations and pre-training of TLMs (23). In addition, the importance of further pre-training with in-domain corpora, a procedure known as continual training (23), has also been documented to yield downstream performance gains (18).

However, even if conceptually simple and empirically powerful, pre-training is challenging and expensive: the relationship between the Transformer architecture, the training corpus, the training hyperparameters, and the evaluation metrics is multi-modal and complex. Furthermore, many have highlighted the importance of previously overlooked design choices in pre-training (such as deciding the pre-training metric and optimizing hyperparameters) that result in significant performance differences.

In this work, our goal is to improve the pre-training procedure of TLMs, by selecting pre-training hyperparameters that result in optimized performance. We argue that an optimized selection of pre-training hyperparameters will accelerate pre-training (i.e., achieve a satisfactory evaluation metric value in fewer epochs) and allow for a better pre-training procedure (i.e., achieve a superior metric value). Increased efficiency in TLM training is all the more important amidst rising concerns pertaining to the carbon footprint of large language models (41); and more specifically, the significant impact hyperparameter choice has on power consumption (43).

Our TLM pre-training use-case is random dynamic masking hyperparameter optimization, contrary to alternative (rule or task-based) MLM dynamic masking approaches, such as SpanBERT (22) and ERNIE (52). Even though (34) showed the efficiency and benefits of random dynamic masking, the selection of the masking probability hyperparameters is often carried out based on heuristics or grid-based search approaches. On the contrary, we investigate automating TLM pre-training hyperparameter selection via multi-armed bandit (MAB) optimization.

We cast the TLM pre-training hyperparameter selection procedure as a sequential decision process, in which at each interaction, an agent selects an action (e.g., pre-training hyperparameters) to maximize cumulative rewards (e.g., pre-training metric). In the dynamic masking use case, the MAB actions (i.e., arms) are the dynamic masking choices, and the masked-language model performance, the unknown function the bandit algorithm is trying to maximize.

Hyperparameter search in machine learning is often addressed as a black-box optimization problem, where the aim is to optimize a computationally expensive function with no additional information known about it. These black-box optimization problems are often solved using evolutionary algorithms (62), entropy search based methods (19, 20), or Bayesian optimization (BO) (12).

BO can tackle the problem of simultaneously optimizing a black-box function with possibly noisy evaluations (50), and of speeding up the allocation of resources to promising hyperparameter configurations, as in (33). We here focus on the former task, and aligned with the successes recently reported by Turner et al. (56) that BO is successful for hyperparameter tuning, propose a BO approach for a sequential tuning of the dynamic masking procedure in MLMs. To that end, we probabilistically model a surrogate for the pre-training objective function and propose a bandit-based technique for its sequential optimization.

Contrary to novel work that aims at deciding which subsets of tokens to mask via combinatorial optimization and dynamic programming (59), we target online learning of appropriate dynamic masking hyperparameters via reinforcement learning (i.e., multi-armed bandit). In addition, and in contrast to approaches that adapt the language model’s masking policy to a particular task of interest (24), we aim to find the sequential set of MLM pre-training choices that result not only on performant pre-trained TLMs, but also best-performing across diverse fine-tuning tasks.

Contributions. The specific contributions of this work are:

- To present a bandit-based generic framework for online, black-box optimization of TLM pre-training.
- To formulate a Gaussian Process based Thompson sampling algorithm for online MLM-loss minimization
of TLMs. The novelty in the presented framework is on fitting the estimated pre-training validation losses with a Gaussian process reward model for the formulation of a Thompson sampling bandit policy, which results in an equivalence between bandit cumulative reward maximization and pre-train loss minimization.

- To showcase empirically that the proposed algorithm efficiently pre-trains TLMs with robust and satisfactory performance, both in pre-training and across diverse downstream fine-tuned tasks.
- To show that sequentially deciding, based on the proposed bandit-based algorithm, how many tokens of the input to mask—and how to mask them—results in improved dynamic masking-based MLM pre-training.

The rest of the manuscript is organized as follows: Section 2 provides a succinct background on Bayesian optimization, the multi-armed bandit and the TLM pre-training procedure; Section 3 describes the proposed method for bandit-based TLM pre-training optimization; with results on its empirical performance evaluated in Section 4, and concluding remarks provided in Section 5.

2 Background

2.1 Bayesian optimization and multi-armed bandits

Bayesian optimization (BO) is a widely used technique to address the problem of hyperparameter optimization in machine learning (20, 50, 56) and many closely related applications in engineering, control systems, materials, and drug discovery (8, 9, 13, 21, 37). BO relies on a probabilistic (providing a measure of uncertainty) surrogate model for the objective function (12, 47) to tackle the fundamentally challenging problem of simultaneously fitting and optimizing a high-dimensional, non-convex function with unknown smoothness, and possibly noisy evaluations. Given the black-box optimization nature of BO, it is of paramount importance that the surrogate model provides a measure of uncertainty, for which generative models, Bayesian neural networks and Gaussian processes are often used (36). Using this surrogate model, an acquisition function determines the most promising point to evaluate next. The multi-armed bandit is a useful framework for addressing this challenge of learning about the environment (i.e., exploration) while simultaneously maximizing the outcomes observed (exploitation).

The multi-armed bandit (MAB) is a well-studied abstraction for problems that require learning while simultaneously maximizing the rewards obtained (30), i.e., balancing the exploration-exploitation tradeoff (31). A MAB is a sequential decision process between an agent and an unknown environment that requires decision-making under uncertainty (45). Mathematically, at each interaction \( t = 1, \ldots , T \), a bandit agent needs to choose an action \( a_t \in A \) from a (not necessarily finite) set of actions \( A \). It then observes a stochastic reward \( r_t \) drawn from an unknown, stochastic distribution \( r_t \sim p(\cdot|a_t) \) of the selected arm \( a_t \). The reward function is in general unknown, dependent on properties often characterized parametrically, i.e., \( p(\cdot|a_t, \theta) \). The goal of a MAB agent is to maximize expected (cumulative) rewards, \( R_T = \sum_{t=1}^{T} \mu_{a_t} \), where we denote each arm’s expected reward as \( \mu_a = \mathbb{E}_{R} \{ r|a, \theta \} \). The challenge in MAB reward maximization is the lack of knowledge about the reward generating model (e.g., its parameters), which demands learning the properties of the reward distribution, as it interacts with the environment.

Bandit algorithms. Since the introduction of the MAB problem by Thompson (53), diverse algorithms have been proposed and analyzed to solve it, from computing optimal strategies for certain types of bandits (15) and probabilistically greedy approaches (4), to upper confidence interval (UCB) (25, 29) and Thompson sampling (46, 54) algorithms. The latter bandit strategies rely on a stochastic model-based view of the MAB, where a reward model is specified with unknown, to be learned parameters. For models in the exponential family, these algorithms have been empirically and theoretically proven to perform competitively (12, 25, 27, 29). Extensions to accommodate reward functions not in the exponential family have also been proposed, by modeling observed rewards via ensembles of plausible models (55), using Gaussian mixture models (57) and Gaussian processes (16, 28, 51), as well as with neural networks (6, 39).

In the context of BO in general, and MABs in particular, reward uncertainty quantification is critical. On the one hand, Riquelme et al. (45) emphasized the need for investigating how to sidestep the slow convergence of the uncertainty estimates in neural network based bandit algorithms. On the other, Gaussian processes (41)
have been shown to provide not only adequate Bayesian uncertainty estimates, but a successful approach to specifying surrogate models that encode smoothness assumptions of the payoff function in different bandit tasks \[7\] [28] [35].

As detailed in Section 3, we resort to a Gaussian process surrogate reward model in the proposed bandit-based optimization of TLM pre-training.

### 2.2 Language model pre-training and the Masked Language Model

Language model pre-training aims at learning language representations that are useful across tasks, i.e., pre-training allows for a model to be better initialized for quick fine-tuning (while avoiding overfitting) to specific downstream tasks. With pre-training, TLMs learn language representations based on the supervision provided by one or more pre-training tasks. A pre-training task is a self-supervised task whose labels are generated automatically. Two popular objectives for TLM pre-training are the Masked Language Model (MLM) and Next Sentence Prediction (NSP).

We focus on MLM pre-training, as initially proposed by Devlin et al. [10], and implemented by many others [28] [34]. MLMs learn by taking an input sequence of words, where a random sample of the tokens is replaced with the special token [MASK], and learning to predict them. I.e., for a given input sequence (with special tokens delimiting them)

\[ [CLS], d_1, \cdots, d_N, [SEP], d_1', \cdots, d_M', [EOS], \]

MLMs select a random sample of the tokens, replace them with the mask, and learn to predict these masked tokens, utilizing both left and right contexts when using TLMs.

**Dynamic masking.** In the original BERT model pre-training [10], a random but static subset of the input sequence tokens is replaced with the mask token. On the contrary, Liu et al. [34] proposed a dynamic masking procedure, which generates a new masking pattern (given a fixed probability of masking) for every sequence fed to the model. Liu et al. [34] demonstrate that this dynamic approach becomes crucial when pre-training for more steps or with larger datasets, attaining better pre-trained and fine-tuned performance. Dynamic masking relies on several hyperparameters, specifically: (i) the probability of replacing an input token with the mask, (ii) the probability that a masked token is unmasked, and (iii) the probability of replacing a token with a random token (instead of with the mask). The online optimization of these dynamic masking hyperparameters is the use-case for our experiments in Section 4.

**MLM pre-training.** In pre-training, one aims at minimizing the MLM loss, which is a function of the original (\(D\)) and masked (\(\widehat{D}\)) datasets, the TLM architecture parameters \(w \in W\), and the hyperparameters \(\psi\) of the pre-training procedure. The MLM objective is the cross-entropy loss for predicting the masked tokens in the masked sequence \(\hat{d} \in \widehat{D}\), where we denote with \(m_l = \{0, 1\}\) the masked tokens in \(\hat{d}\) for tokens \(l = 1, \cdots, L\), in the original input sequence \(d \in D\). Mathematically,

\[
y = l(d, \hat{d}; w, \psi) = -\log p(d|\hat{d}; w, \psi)
\]

\[
= - \sum_{l=1}^{L} m_l \log p(l_{d}|\hat{l}_{d}; w, \psi) = - \sum_{l=1}^{L} m_l \log \left( \frac{\exp \left( h(\hat{l}_{d}; w, \psi)\top e(l_{d}) \right)}{\sum_{t=1}^{L} \exp \left( h(\hat{l}_{t}; w, \psi)\top e(l_{t}) \right)} \right)
\]

where we explicitly indicate with \(\psi\) the dependency with respect to all hyperparameters relevant in pre-training and optimization procedures.

The analytical form of the MLM loss function, which is a function of the hyperparameters \(\psi\) used and the data where it is evaluated, is in general complex and unknown. However, estimates of the MLM loss are available at every epoch \(e\) of pre-training, i.e., an empirical estimate \(\hat{y}_e\) of the MLM loss can be computed. For the sake of fair comparisons under different training setups (e.g., mini-batch sizes or other hyperparameters), per-epoch averaged empirical MLM losses are computed in the validation dataset \(D_{val}\),

\[
\bar{y} = \bar{l}(D_{val}, \widehat{D}_{val}; w, \psi) = - \sum_{d \in D_{val}} \sum_{l=1}^{L} m_l \log p(l_{d}|\hat{l}_{d}; w, \psi) \sum_{l=1}^{L} m_l .
\]
The pre-training objective is to find the TLM architecture that minimizes the MLM loss for the whole dataset $D$ and its masked version $\hat{D}$. In practice, this minimization is commonly executed via stochastic gradient-descent methods, run for $e = 1, \cdots, E$, epochs with randomly drawn mini-batches $D_b \in D$,

$$\hat{w}_c = \arg\min_{w \in W} l(D_b, \hat{D}_b; w, \psi) = -\arg\min_{w \in W} \sum_{d \in D_b} \sum_{l=1}^{L} m_l \log p(l_d|\hat{d}; w, \psi).$$

3 Proposed method

We hereby propose to optimize the TLM pre-training procedure by casting it as a sequential decision process, where we tackle the problem of sequentially fitting and optimizing a pre-training black-box loss function with noisy evaluations. We pose the task of TLM pre-training with noisy MLM loss observations as a multi-armed bandit problem. We first determine the appropriate action space, and then formulate a proper surrogate reward function (leveraging the observed empirical MLM validation losses) that the bandit maximizes for its sequential selection of arms.

We define pre-training steps (i.e., a fixed number of stochastic gradient updates $l$) as bandit interactions $t = 1, \cdots, T$, towards minimizing a TLM pre-training objective $l(\cdot|\psi)$ given tunable hyperparameters $\psi$ — with (stochastic) objective evaluations estimated in the validation set. In the use-case of MLM pre-training with dynamic masking, in each bandit interaction, one selects the hyperparameters $\psi$ (e.g., the number of tokens to mask and associated random masking probabilities), pre-trains the TLM for certain stochastic updates $u$ that minimize the MLM loss as in Equation (5), and evaluates the pre-trained model’s MLM performance in the validation subset as per Equation (4). To that end, we identify the pre-training hyperparameters at interaction $t$, $\psi_t$, as the bandit’s arms, i.e., $a_t = \psi_t$.

Due to the black-box nature of the pre-training objective (with only stochastic evaluations available), we formulate below the stochastic reward function surrogate needed to formalize the MAB approach to online optimization of TLM pre-training.

3.1 From MLM pre-training to Gaussian process based regret minimization

We hereby devise a bandit reward function that results in the sequential optimization of the MLM pre-training objective. To that end, we transform the empirical pre-training validation loss for each pre-training interaction into a reward quantity that allows for its cumulative optimization. To accommodate the empirical, stochastic loss estimates collected from the unknown analytical form of the loss function, we resort to Gaussian process modeling.

**Bandit rewards as empirical MLM loss differences.** To guarantee that the cumulative rewards a bandit agent maximizes result in minimization of the pre-training objective, we compute the observed empirical rewards as the difference in averaged MLM losses between bandit interactions, i.e.,

$$r_t(\psi_t) = [-\bar{y}_t(D_{val}, \hat{D}_{val}; \psi_t)] - [-\bar{y}_{t-1}(D_{val}, \hat{D}_{val}; \psi_{t-1})],$$

where we have dropped the dependency of the MLM loss with respect to the TLM parameters $w$ for ease of exposition.

We now show that maximizing the cumulative rewards as defined above is equivalent to minimizing the training loss at interaction $T$. First, we compute the cumulative rewards,

$$R_T = \sum_{t=1}^{T} r_t(a_t, z_t) = \sum_{t=1}^{T} (-\bar{y}_t) - (-\bar{y}_{t-1})$$

$$= (-\bar{y}_1) - (-\bar{y}_0) + (-\bar{y}_2) - (-\bar{y}_1) + (-\bar{y}_3) - (-\bar{y}_2) + (-\bar{y}_4) - (-\bar{y}_3) + \cdots$$

$$+ (-\bar{y}_{T-3}) - (-\bar{y}_{T-2}) + (-\bar{y}_{T-2}) - (-\bar{y}_{T-1}) + (-\bar{y}_{T-1}) - (-\bar{y}_{T-2}) + (-\bar{y}_{T}) - (-\bar{y}_{T-1})$$

$$= \bar{y}_0 - \bar{y}_T,$$

1Note that $u$ stochastic gradient updates might or might not correspond to a full pre-training epoch $e$. 

5
where $y_0$ is a constant, initial loss of a randomly initialized model. We then conclude that maximizing cumulative rewards

$$\max R_T = \max (\bar{y}_0 - \bar{y}_T) = \max -\bar{y}_T$$

(9)

$$= \min \bar{y}_T = \min \bar{y}_T(D_{val}, D_{val}; \psi_T)$$

(10)

is equivalent to minimizing validation MLM loss. Therefore, a bandit agent that aims at maximizing the cumulative rewards as in Equation (7) minimizes the MLM pre-training objective of Equation (4).

**Bandit reward functions as Gaussian process models.** In practice, TLM pre-training is carried out based on empirical risk minimization: i.e., only empirical estimates $\bar{y}_t$ of the true MLM objective are available. Namely, rewards as defined in Equation (6) are stochastic draws from an analytically unknown objective function, $\bar{y}_t \sim I(\psi_t)$. To accommodate these stochastic observations of the unknown loss function —that we aim at optimizing with respect to its hyperparameters $\psi$— we model the bandit reward function via a Gaussian process $f$, with the observed (stochastic) rewards independent and identically (i.i.d.) distributed as

$$r_t(\psi_t) = f(\psi_t; \theta) + \epsilon_t$$

(11)

where $f(\cdot; \theta)$ is a Gaussian process (GP) surrogate model of the pre-training objective, and $\epsilon_t$ denotes the stochastic nature of each of the observed rewards —as empirical estimates computed in Equation (6). In summary, we overcome the black-box nature of the pre-training objective function (e.g., the MLM loss) by modeling the observed rewards as realizations of a noisy surrogate GP model.

**Gaussian process.** A collection of random variables $f(\psi) : \psi \in \Psi$ is said to be drawn from a GP with mean function $\mu(\cdot)$ and covariance function $k(\cdot, \cdot)$, if for any finite set of elements $\psi_1, \cdots, \psi_k \in \Psi$, the associated finite set of random variables $f(\psi_1), \cdots, f(\psi_k)$, follows

$$f(\psi) \sim GP(\mu(\cdot), k(\cdot, \cdot))$$

(12)

with

$$\begin{cases} 
\mu(\psi) = \mathbb{E}[f(\psi)], \\
k(\psi, \psi') = \mathbb{E}[(f(\psi) - \mu(\psi))(f(\psi') - \mu(\psi'))].
\end{cases}$$

In particular, a GP is a stochastic process such that any finite collection of random variables has a multivariate Gaussian distribution (14). A GP can be seen as a probability distribution over arbitrary functions, with $\mu(\cdot)$ its mean function, and $k(\cdot, \cdot)$ the covariance kernel.

**GP model fitting.** The mean and kernel functions determine the GP function class: i.e., the regularity/smoothness assumptions of the modeled data. These are parameterized prior-functions $\mu(\cdot; \theta_\mu)$ and $k(\cdot, \cdot; \theta_k)$ with $\theta = (\theta_\mu, \theta_k)$, which can be fitted to the observed data $r_{1:T} = (r_1, \cdots, r_T)$ at inputs $\psi_{1:T} = (\psi_1, \cdots, \psi_T)$. For instance, via Type-II maximum likelihood estimation (MLE) of the GP model $f(\cdot; \theta)$’s hyperparameters $\theta,$

$$\hat{\theta} = \arg \max_{\theta} \log p(r_{1:T} | f(\psi_{1:T} | \theta))$$

(13)

where the data likelihood $p(r | f, \theta)$ is a function of the observation noise’s probability distribution. Bayesian approaches to hyperparameter selection for GP model training can also be implemented (14).

**Gaussian process posteriors.** Given a fitted GP, posterior inference —computing the predictive distribution of a new datapoint $\psi'$ after observing $\psi_{1:T}$— can be performed in closed form for the Gaussian observation noise case: i.e., when the noise in Equation (11) is i.i.d. drawn $\epsilon_t \sim N(0, \sigma^2)$. Formally, for a given set of observations $r_{1:T} = (r_1, \cdots, r_T)$ at inputs $\psi_{1:T} = (\psi_1, \cdots, \psi_T)$, the posterior distribution over $f$ is a GP with the following mean and covariance functions:

$$\mu_T(\psi) = k_T(\psi)\mathcal{T}(K_T + \sigma^2 I)^{-1}r_{1:T},$$

(14)

$$k_T(\psi, \psi') = k(\psi, \psi') - k_T(\psi)\mathcal{T}(K_T + \sigma^2 I)^{-1}k_T(\psi'),$$

(15)

with

$$\begin{cases} k_T(\psi) = (k(\psi_1, \psi), \cdots, k(\psi_T, \psi))^\top, \\
K_T = (k(\psi, \psi'))_{\psi, \psi' \in \psi_{1:T}}.
\end{cases}$$

(16)

These closed-form posterior inference expressions can be efficiently computed, both in exact and approximate ways (12, 14). Posterior inference with observation noise beyond the Gaussian assumption is an active research area, with many approximate techniques available for practitioners (11, 49, 55, 61).
3.2 GP-Thompson sampling for TLM pre-training.

Leveraging the GP-based reward model in Equation (11) and defining pre-training hyperparameters $\psi_t$ as the bandit arms, $a_t = \psi_t$, we propose a bandit-based method for online pre-training loss minimization. Namely, we propose a Thompson sampling (TS) bandit algorithm that sequentially decides what arm $a_t$ to play at each sequential interaction $t = 1, \cdots, T$, by drawing from the GP posterior updated with all available data up to interaction $t$, to maximize its cumulative rewards as defined in Equation (7).

The proposed GP-TS bandit algorithm —with pseudo-code provided in Algorithm 1— views the TLM pre-training procedure as an unknown black-box function with inputs $a_t = \psi_t$ and outputs $r_t(\psi_t)$ as in Equation (11) —for which cumulative rewards need to be maximized.

We note that any TLM can be used within our proposed framework, as long as the pre-training hyperparameter space $\psi \in \Psi$ is identified, and rewards as in Equation (6) can be computed based on a given pre-training objective. The GP reward model in Equation (11) accommodates continuous arms $a_t$, with dimensionality determined by the TLM pre-training hyperparameter space $\Psi$.

**Algorithm 1** GP-TS for online optimization of TLM pre-training

1. **Input**: TLM and training corpus
2. **Input**: Pre-training hyperparameter space $\Psi$
3. **Input**: Number of bandit pre-training interactions $T$, number of updates per-interaction $u$
4. **Input**: GP prior functions $\mu(\cdot)$ and $k(\cdot, \cdot)$, initial hyperparameters $\theta_0$
5. **Initialize**: $\mathcal{A} = \Psi$, $\hat{\theta}_1 = \theta_0$, $\mathcal{H}_1 = \emptyset$
6. **for** $t = 1, \cdots, T$ **do**
7. **Draw** posterior sample from the posterior GP, i.e., $\mu_a^{(t)} \sim f(\mu_t(a|\hat{\theta}_t), k_t(a, a'|\hat{\theta}_t))$.
8. **Select** arm based on drawn posterior sample, i.e., $a_t = \arg\max_{a' \in \mathcal{A}} P(a'|\mu_a^{(t)}, k_t(a, a'|\hat{\theta}_t))$.
9. **Run** TLM pre-training for $u$ steps, with hyperparameters $\psi_t = a_t$.
10. **Compute** validation loss of pre-trained TLM, i.e., $\bar{y_t}$ as in Equation (4).
11. **Observe** bandit reward, i.e., $r_t$ as in Equation (6).
12. **Update** bandit history $\mathcal{H}_{1:t} = \mathcal{H}_{1:t-1} \cup \{a_t, r_t\}$
13. **Fit** GP model with $\mathcal{H}_{1:t}$, i.e., $\hat{\theta}_{t+1} = \arg\max_\theta \log p(r_{1:t}|f(a_{1:t}), \theta)$.
14. **end for**

**GP-TS policy.** To execute the proposed GP-Thompson sampling policy [12, 54], we compute the GP reward model posterior, with sufficient statistics as in Equation (10) —which due to its Gaussian nature permits drawing of predictive samples from it, as in Step 6 of Algorithm 1. These samples are used in the proposed GP-TS to determine (in Step 7 of Algorithm 1) the sequential arms (hyperparameters $a_t = \psi_t$) for the next interaction of the pre-training procedure.

After $u$ pre-training steps of the TLM, we collect the pre-trained model’s MLM validation loss to compute the observed bandit rewards $r_t$ as in Equation (6). After every bandit interaction $t$, new evidence is collected that allows for updating (i.e., re-fitting) the GP model to the observed input (action)-output (rewards) history $\mathcal{H}_{1:t}$. For instance, via Type-II MLE —although we acknowledge that other hyperparameter selection procedures might be used—as in Step 12 of Algorithm 1.

4 Experiments

4.1 Evaluation set-up

**Implementation.** We implement Algorithm 1 in Python with Gaussian process modules based on GPyTorch [14]. Our use-case for evaluating the proposed method is the online optimization of the dynamic masking procedure of TLM pre-training, as argued for by Liu et al. [41] in their RoBERTa model. We implement the RoBERTa model as provided by Fairseq [40] and incorporate it as a module in our proposed framework.

\^Our implementation of the proposed bandit-based framework will be made publicly available in a public Github repository upon acceptance.
RoBERTa’s dynamic masking procedure relies on several hyperparameters $\psi$, specifically: $\rho$, the probability of replacing an input token with the mask; $\gamma$ the probability that a masked token is left unmasked; and $\lambda$, the probability of replacing a token with a random token (instead of with the mask).

**Experiment set-up.** Our goal is to probe the ability of the proposed GP-TS method to —given a dataset, a TLM architecture, and a computational budget— efficiently pre-train the best-performing language model, with satisfactory performance in pre-training and downstream tasks. We replicate the pre-training described in (34) and compare the performance of different RoBERTa models.

We download, pre-process and encode the [Wikitext 103](dataset) dataset for pre-training, from scratch, each of the candidate TLMs. To quantify the downstream capabilities of the pre-trained models, we evaluate their performance in the General Language Understanding Evaluation (GLUE) benchmark (60).

We run our experiments with RoBERTa models using the BERT-base architecture (125M parameters) in a server with 8 Tesla V100-SXM2-32GB GPUs —implementation and configuration details are provided in Appendix A. The aim is not to compare these models with large-scale TLMs trained in huge datasets, but to scrutinize the quality of pre-trained RoBERTa models under equal experimental conditions. To that end, we fix the seed for the execution of RoBERTa pre-training and fine-tuning, but run five different realizations of the proposed GP-TS: i.e., we quantify the performance variability induced by the stochastic bandit decisions.

In Section 4.2 below, we evaluate the difference between RoBERTa models pre-trained based on a grid-search over masking probabilities $\rho$ —as originally executed by Liu et al. (34)— to our proposed bandit-based online optimization procedure —the proposed GP-TS in Algorithm 1. After showing the benefits of GP-TS based sequential selection of the masking probability $\rho$, we investigate in Section 4.3 how successful the bandit-based optimization is when selecting all dynamic masking hyperparameters, $\psi = (\rho, \gamma, \lambda)$.

### 4.2 GP-TS for online optimization of the masking probability

We first focus on the online optimization of the masking probability $\rho$, with fixed, default $\gamma = 0.1$ and $\lambda = 0.1$ values as per guidelines in (34). The masking probability search space is $\Psi = (0, 0.5)$, with a regular interval of 0.05 for the proposed GP-TS method.

**Pre-training performance.** Results in Figure 1, where we compare the MLM loss computed in the validation set over each of the pre-training epochs (a bandit interaction equals a single epoch), demonstrate that the proposed GP-TS pre-trains the best performing RoBERTa model.

The benefits provided are not only on the attained lower MLM metric value, but on a faster pre-training procedure: a better model than grid-search based alternatives is found in less than 50 epochs. The RoBERTa model with the best MLM loss is pre-trained by GP-TS in about 60 epochs, with no significant performance improvements past 75 pre-training epochs. Namely, the selected RoBERTa architecture, when pre-trained in a given dataset, achieves the best MLM loss in fewer epochs when pre-trained with the proposed GP-TS.

In addition, we observe that GP-TS avoids model overfitting: contrary to RoBERTa models pre-trained with fixed $\rho$ that result in V-shaped validation curves (MLM training loss values are provided in Appendix B.1), the GP-TS pre-trained RoBERTa model showcases minimal degradation over pre-training epochs.

All in all, Figure 1 exhibits how the proposed GP-TS is able to sequentially select dynamic masking probabilities $\rho$ that result in fast, robust, and accurate pre-trained models.

**Fine-tuning performance.** We showcase the downstream benefits of pre-trained TLMs by evaluating their accuracy in GLUE tasks, after fine-tuning each of the pre-trained language models for just two epochs. To elucidate the pre-trained language models’ quality over pre-training steps, we fine-tune and evaluate each RoBERTa model after every pre-training epoch: i.e., the x-axis in Figure 2 is identical to the x-axis in Figure 1.

Figure 2 showcases that the GP-TS pre-trained model, after only two fine-tuning epochs, provides the best GLUE-QQP task performance —results for all GLUE tasks are provided in Appendix B.2. We note that the downstream performance benefit is most evident after 60 epochs of pre-training, i.e., as soon as best MLM-based pre-trained models have been learned by GP-TS, as shown in Figure 1.

The accuracy of all pre-trained RoBERTa models in all GLUE tasks, after pre-training for 75 epochs and fine-tuning for only two epochs per-task, is shown in Table 1. Results in Table 1 exhibit how the proposed GP-TS pre-trains language models that can then be quickly fine-tuned to downstream tasks with top accuracy.
Figure 1: MLM validation loss performance comparison (lower is better) of grid-search based and the GP-TS based pre-trained RoBERTa models. GP-TS results are averaged across five realizations, with standard deviation shown in the shaded area.

Figure 2: GLUE QQP task accuracy comparison (higher is better) after two fine-tuning epochs of grid-search based and the GP-TS based pre-trained RoBERTa models.
Table 1: GLUE task accuracy (higher is better) for models at pre-training epoch 75, subsequently fine-tuned for two epochs. STS-B is evaluated via the Pearson correlation coefficient.

| Model   | CoLA | MNLI | MRPC | QNLI | QQP | RTE | SST-2 | STS-B |
|---------|------|------|------|------|-----|-----|-------|-------|
| $\rho = 0.05$ | 0.689 | 0.613 | 0.706 | 0.66 | 0.763 | 0.473 | 0.795 | 0.143 |
| $\rho = 0.10$ | **0.691** | 0.642 | 0.694 | 0.687 | 0.773 | 0.48 | 0.79 | 0.247 |
| $\rho = 0.15$ | 0.687 | 0.657 | 0.703 | 0.79 | 0.781 | 0.477 | 0.807 | 0.225 |
| $\rho = 0.20$ | 0.685 | 0.667 | 0.699 | 0.787 | 0.788 | 0.48 | 0.808 | 0.314 |
| $\rho = 0.25$ | 0.675 | 0.661 | 0.691 | 0.787 | 0.788 | **0.502** | **0.819** | 0.248 |
| GP-TS $\psi = \rho$ | 0.69 | **0.669** | **0.708** | **0.791** | **0.801** | 0.491 | 0.812 | **0.353** |

Overall, the presented empirical evidence illustrates that the proposed GP-TS enables fast and superior pre-training of language models: not only is GP-TS able to improve the MLM pre-training objective, but it results in robust TLMs that can be quickly fine-tuned to downstream tasks with excellent accuracy performance. These results show that instead of pre-training with fixed masking probabilities, sequentially deciding how many input tokens to mask —as per the GP-TS that minimizes MLM loss— is beneficial.

4.3 GP-TS for online optimization of all dynamic masking hyperparameters

We now interrogate the capability of the proposed GP-TS in optimizing TLMs with respect to all hyperparameters $\psi = (\rho, \gamma, \lambda)$ of the dynamic masking procedure. For these experiments, we focus on the hypercube space $\Psi = (0, 0.25)^3$, and compare its performance to the GP-TS method that searches only along $\rho \in (0, 0.5)$, with default $\gamma = 0.1$ and $\lambda = 0.1$ values. The goal is to inspect whether the proposed method is able to autonomously pre-train a RoBERTa model when no knowledge about what dynamic masking hyperparameters to use is available.

Figure 3: MLM validation loss performance comparison (lower is better) of GP-TS based pre-trained models, when $\psi = \rho$ and $\psi = (\rho, \gamma, \lambda)$. GP-TS results are averaged across five realizations, with standard deviation shown in the shaded area.

As shown in Figure 3, the proposed GP-TS is successful, even when operating over a 3-dimensional search space, of finding a sequence of hyperparameters $\alpha_t = \psi_t$ that result in a best-performing RoBERTa model.
We also observe that successful pre-training is achieved faster: i.e., a lower MLM loss is attained when pre-training with GP-TS $\psi = (\rho, \gamma, \lambda)$ than with the GP-TS $\psi = \rho$ (in as few as 60 epochs, with no significant performance improvement beyond 75 epochs). The GP-TS pre-trained model is again easily fine-tuned to provide satisfactory downstream performance across all GLUE tasks, as reported in Table 2.

| Model               | CoLA | MNLI | MRPC | QNLI | QQP | RTE | SST-2 | STS-B |
|---------------------|------|------|------|------|-----|-----|-------|-------|
| GP-TS $\psi = \rho$ | 0.69 | 0.669| 0.708| 0.791| 0.801| 0.491| 0.812 | 0.353 |
| GP-TS $\psi = (\rho, \gamma, \lambda)$ | 0.69 | 0.665| 0.699| 0.778| 0.796| 0.477| 0.836 | 0.325 |

Based on the presented results, we conclude that the proposed GP-TS is able to successfully find sequences of dynamic masking hyperparameters —even when no good guesses for them are available— that minimize MLM pre-training loss. Instead of pre-training with fixed dynamic masking hyperparameters, our results indicate that the proposed GP-TS algorithm sequentially selects hyperparameters that result in robust and well-performing models.

5 Conclusion

We have presented a multi-armed bandit-based online optimization framework for the sequential selection of pre-training hyperparameters towards optimized Transformer-based language model performance.

We model noisy evaluations of the pre-training objective function (e.g., the MLM loss) as drawn from a surrogate Gaussian process, and propose a Gaussian process based Thompson sampling (GP-TS) for online MLM-loss minimization. We prove the equivalence between the proposed bandit reward function’s cumulative maximization and pre-training loss minimization.

We provide empirical evidence of how the proposed GP-TS, when applied to MLM dynamic masking optimization, results in robust and accurate language models. Notably, while (34) randomly select which input tokens to mask with fixed probability, we show that sequentially adapting the masking hyperparameters as determined by GP-TS results in superior performance.

Our experiments demonstrate not only the practical significance of the proposed method in terms of efficiency (i.e., successful pre-training in less epochs), but that GP-TS based models achieve superior performance in pre-training (i.e., reduced MLM loss) and across diverse downstream tasks.

Building upon our formulation and the provided evidence, we envision interesting follow-up work on showcasing the proposed method’s ability to successfully pre-train large-scale models in general purpose corpora, as well as for domain-specific models and tasks.

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A Implementation details

A.1 Gaussian process

We implement Gaussian process modules based on GPyTorch \(^{[14]}\), and execute all experiments with a GP process prior and GP fitting details as described in Table 3.

Table 3: Gaussian Process prior and hyperparameters.

| Hyperparameter         | Initial Value |
|------------------------|---------------|
| GP Model               |               |
| Mean Function          | Constant      |
| Prior constant         | 0             |
| Kernel Function        | Scaled RBF Kernel |
| Prior output-scale     | 1             |
| Prior length-scale     | 0.25          |
| Observation Model      |               |
| Likelihood function    | Gaussian      |
| Noise variance         | 1             |
| Training details       |               |
| Loss function          | ExactMarginalLogLikelihood |
| train max iters        | 100           |
| loss epsilon           | 0.01          |
| Optimizer              |               |
| optimizer              | adam          |
| lr                     | 0.1           |
A.2 RoBERTa pre-training

We execute the RoBERTa pre-training procedure as described in Fairseq’s RoBERTa pre-training tutorial, with specific hyperparameters as described in Table 4.

Table 4: RoBERTa pre-training hyperparameters.

| Hyperparameter          | Value          |
|-------------------------|----------------|
| Architecture            | RoBERTa base   |
| Task                    | masked lm      |
| Criterion               | masked lm      |
| dropout                 | 0.1            |
| attention-dropout       | 0.1            |
| weight-decay            | 0.01           |
| batch-size              | 16             |
| update-freq             | 16             |
| sample-break-mode       | complete       |
| tokens-per-sample       | 512            |
| optimizer               | adam           |
| adam-betas              | (0.9,0.98)     |
| adam-eps                | 1e-6           |
| clip-norm               | 1.0            |
| lr                      | 0.001          |
| lr-scheduler            | polynomial decay |
| linear-warmup-updates   | 1000           |
| mask-prob               | ρ              |
| leave-unmasked-prob     | 0.1            |
| random-token-prob       | 0.1            |
A.3 RoBERTa fine-tuning

We execute the RoBERTa fine-tuning procedure for GLUE tasks as described in Fairseq’s RoBERTa GLUE tutorial, with specific hyperparameters as described in Tables 5-12.

Table 5: RoBERTa fine-tuning hyperparameters for CoLA.

| Hyperparameter          | Value                                      |
|-------------------------|--------------------------------------------|
| Architecture            | RoBERTa base                               |
| Task                    | sentence prediction                        |
| Criterion               | sentence prediction                        |
| num-classes             | 2                                          |
| max-epoch               | 2                                          |
| dropout                 | 0.1                                        |
| attention-dropout       | 0.1                                        |
| weight-decay            | 0.1                                        |
| batch-size              | 16                                         |
| update-freq             | 1                                          |
| required-batch-size-multiple | 1                                    |
| sample-break-mode       | complete                                   |
| tokens-per-sample       | 512                                        |
| max-update              | 534                                        |
| max-tokens              | 4400                                       |
| max-positions           | 512                                        |
| optimizer               | adam                                       |
| adam-betas              | (0.9,0.98)                                 |
| adam-eps                | 1e-6                                       |
| clip-norm               | 1.0                                        |
| lr                      | 1e-5                                       |
| lr-scheduler            | polynomial decay                          |
| linear-warmup-updates   | 32                                         |
| total-num-update        | 534                                        |
| init-token              | 0                                          |
| separator-token         | 2                                          |
Table 6: RoBERTa fine-tuning hyperparameters for MNLI.

| Hyperparameter       | Value        |
|----------------------|--------------|
| Architecture         | RoBERTa base |
| Task                 | sentence prediction |
| Criterion            | sentence prediction |
| num-classes          | 3            |
| max-epoch            | 2            |

**Model details**

| Hyperparameter       | Value |
|----------------------|-------|
| dropout              | 0.1   |
| attention-dropout    | 0.1   |
| weight-decay         | 0.1   |

**Training details**

| Hyperparameter       | Value |
|----------------------|-------|
| batch-size           | 32    |
| update-freq          | 1     |
| required-batch-size-multiple | 1     |
| sample-break-mode    | complete |
| tokens-per-sample    | 512   |
| max-update           | 12387 |
| max-tokens           | 4400  |
| max-positions        | 512   |

**Optimizer**

| Hyperparameter       | Value        |
|----------------------|--------------|
| optimizer            | adam         |
| adam-betas           | (0.9, 0.98)  |
| adam-eps             | 1e-6         |
| clip-norm            | 1.0          |

**Learning rate**

| Hyperparameter       | Value |
|----------------------|-------|
| lr                   | 1e-5  |
| lr-scheduler         | polynomial decay |
| linear-warmup-updates | 743   |
| total-num-update     | 12387 |

**Other**

| Hyperparameter       | Value |
|----------------------|-------|
| init-token           | 0     |
| separator-token      | 2     |
Table 7: RoBERTa fine-tuning hyperparameters for MRPC.

| Hyperparameter        | Value                        |
|-----------------------|------------------------------|
| Architecture          | RoBERTa base                 |
| Task                  | sentence prediction          |
| Criterion             | sentence prediction          |
| num-classes           | 2                            |
| max-epoch             | 2                            |
| dropout               | 0.1                          |
| attention-dropout     | 0.1                          |
| weight-decay          | 0.1                          |
| batch-size            | 16                           |
| update-freq           | 1                            |
| required-batch-size-multiple | 1                        |
| sample-break-mode     | complete                     |
| tokens-per-sample     | 512                          |
| max-update            | 230                          |
| max-tokens            | 4400                         |
| max-positions         | 512                          |
| optimizer             | adam                         |
| adam-betas            | (0.9, 0.98)                  |
| adam-eps              | 1e-6                         |
| clip-norm             | 1.0                          |
| lr                    | 1e-5                         |
| lr-scheduler          | polynomial decay             |
| linear-warmup-updates | 13                           |
| total-num-update      | 230                          |
| init-token            | 0                            |
| separator-token       | 2                            |
Table 8: RoBERTa fine-tuning hyperparameters for QNLI.

| Hyperparameter     | Value                      |
|--------------------|----------------------------|
| Architecture       | RoBERTa base              |
| Task               | sentence prediction        |
| Criterion          | sentence prediction        |
| num-classes        | 2                         |
| max-epoch          | 2                         |
| Model details      |                            |
| dropout            | 0.1                       |
| attention-dropout  | 0.1                       |
| weight-decay       | 0.1                       |
| Training details   |                            |
| batch-size         | 32                        |
| update-freq        | 1                         |
| required-batch-size-multiple | 1          |
| sample-break-mode  | complete                  |
| tokens-per-sample  | 512                       |
| max-update         | 3311                      |
| max-tokens         | 4400                      |
| max-positions      | 512                       |
| Optimizer          |                            |
| optimizer          | adam                      |
| adam-betas         | (0.9, 0.98)               |
| adam-eps           | 1e-6                      |
| clip-norm          | 1.0                       |
| Learning rate      |                            |
| lr                 | 1e-5                      |
| lr-scheduler       | polynomial decay          |
| linear-warmup-updates | 199                |
| total-num-update   | 3311                      |
| Other              |                            |
| init-token         | 0                         |
| separator-token    | 2                         |
Table 9: RoBERTa fine-tuning hyperparameters for QQP.

| Hyperparameter       | Value                  |
|----------------------|------------------------|
| **Architecture**     | RoBERTa base           |
| **Task**             | sentence prediction    |
| **Criterion**        | sentence prediction    |
| **num-classes**      | 2                      |
| **max-epoch**        | 2                      |
| **Model details**    |                        |
| dropout              | 0.1                    |
| attention-dropout    | 0.1                    |
| weight-decay         | 0.1                    |
| **Training details** |                        |
| batch-size           | 32                     |
| update-freq          | 1                      |
| required-batch-size-multiple | 1               |
| sample-break-mode    | complete               |
| tokens-per-sample    | 512                    |
| max-update           | 11327                  |
| max-tokens           | 4400                   |
| max-positions        | 512                    |
| **Optimizer**        |                        |
| optimizer            | adam                   |
| adam-betas           | (0.9,0.98)             |
| adam-eps             | 1e-6                   |
| clip-norm            | 1.0                    |
| **Learning rate**    |                        |
| lr                   | 1e-5                   |
| lr-scheduler         | polynomial decay       |
| linear-warmup-updates| 2832                   |
| total-num-update     | 11327                  |
| **Other**            |                        |
| init-token           | 0                      |
| separator-token      | 2                      |
Table 10: RoBERTa fine-tuning hyperparameters for RTE.

| Hyperparameter     | Value            |
|--------------------|------------------|
| Architecture       | RoBERTa base     |
| Task               | sentence prediction |
| Criterion          | sentence prediction |
| num-classes        | 2                |
| max-epoch          | 2                |
| **Model details**  |                  |
| dropout            | 0.1              |
| attention-dropout  | 0.1              |
| weight-decay       | 0.1              |
| **Training details**|                |
| batch-size         | 16               |
| update-freq        | 1                |
| required-batch-size-multiple | 1        |
| sample-break-mode  | complete         |
| tokens-per-sample  | 512              |
| max-update         | 204              |
| max-tokens         | 4400             |
| max-positions      | 512              |
| **Optimizer**      |                  |
| optimizer          | adam             |
| adam-betas         | (0.9,0.98)       |
| adam-eps           | 1e-6             |
| clip-norm          | 1.0              |
| **Learning rate**  |                  |
| lr                 | 2e-5             |
| lr-scheduler       | polynomial decay |
| linear-warmup-updates | 12              |
| total-num-update   | 204              |
| **Other**          |                  |
| init-token         | 0                |
| separator-token    | 2                |
Table 11: RoBERTa fine-tuning hyperparameters for SST.

| Hyperparameter       | Value                  |
|----------------------|------------------------|
| Architecture         | RoBERTa base           |
| Task                 | sentence prediction    |
| Criterion            | sentence prediction    |
| num-classes          | 2                      |
| max-epoch            | 2                      |
| dropout              | 0.1                    |
| attention-dropout    | 0.1                    |
| weight-decay         | 0.1                    |
| batch-size           | 32                     |
| update-freq          | 1                      |
| required-batch-size-multiple | 1                 |
| sample-break-mode    | complete               |
| tokens-per-sample    | 512                    |
| max-update           | 2093                   |
| max-tokens           | 4400                   |
| max-positions        | 512                    |
| optimizer            | adam                   |
| adam-betas           | (0.9,0.98)             |
| adam-eps             | 1e-6                   |
| clip-norm            | 1.0                    |
| lr                   | 1e-5                   |
| lr-scheduler         | polynomial decay       |
| linear-warmup-updates | 125                |
| total-num-update     | 2093                   |
| init-token           | 0                      |
| separator-token      | 2                      |
Table 12: RoBERTa fine-tuning hyperparameters for STS-B.

| Hyperparameter        | Value                      |
|-----------------------|----------------------------|
| Architecture          | RoBERTa base               |
| Task                  | sentence prediction        |
| Criterion             | sentence prediction        |
| num-classes           | 1 (regression-target)      |
| max-epoch             | 2                          |
| **Model details**     |                            |
| dropout               | 0.1                        |
| attention-dropout     | 0.1                        |
| weight-decay          | 0.1                        |
| **Training details**  |                            |
| batch-size            | 16                         |
| update-freq           | 1                          |
| required-batch-size-multiple | 1               |
| sample-break-mode     | complete                   |
| tokens-per-sample     | 512                        |
| max-update            | 360                        |
| max-tokens            | 4400                       |
| max-positions         | 512                        |
| **Optimizer**         |                            |
| optimizer             | adam                       |
| adam-betas            | (0.9,0.98)                 |
| adam-eps              | 1e-6                       |
| clip-norm             | 1.0                        |
| **Learning rate**     |                            |
| lr                    | 2e-5                       |
| lr-scheduler          | polynomial decay           |
| linear-warmup-updates | 21                         |
| total-num-update      | 360                        |
| **Other**             |                            |
| init-token            | 0                          |
| separator-token       | 2                          |
B Additional results

B.1 Pre-training losses

We showcase in Figures 4 and 5 the pre-training MLM losses over epochs computed both in the training and validation datasets, where we observe overfitting for RoBERTa models with fixed hyperparameters, yet robust learning for the proposed GP-TS technique.

![Figure 4: MLM loss performance comparison (lower is better) of grid-search based and the GP-TS based pre-training with respect to $\rho$. GP-TS results are averaged across 5 realizations, with standard deviation shown in the shaded area.](image)

Figure 4: MLM loss performance comparison (lower is better) of grid-search based and the GP-TS based pre-training with respect to $\rho$. GP-TS results are averaged across 5 realizations, with standard deviation shown in the shaded area.

![Figure 5: MLM loss performance comparison (lower is better) of the GP-TS based pre-trained models, when $\psi = \rho$ and $\psi = (\rho, \gamma, \lambda)$. GP-TS results are averaged across 5 realizations, with standard deviation shown in the shaded area.](image)

Figure 5: MLM loss performance comparison (lower is better) of the GP-TS based pre-trained models, when $\psi = \rho$ and $\psi = (\rho, \gamma, \lambda)$. GP-TS results are averaged across 5 realizations, with standard deviation shown in the shaded area.

B.2 Fine-tuning losses

We showcase in Figure 6 the accuracy in all GLUE task dev sets, after fine-tuning each of the pre-trained language models for only two fine-tuning epochs. We note that the downstream performance in GLUE-tasks with small datasets (i.e., CoLA, MRPC, RTE) is unsatisfactory (for both fixed $\rho$ and GP-TS pre-trained models) when run with the hyperparameters as in Appendix A.3. Although further experimentation is required to improve downstream performance in these GLUE tasks, our claim that GP-TS provides pre-trained models easily fine-tunable to a variety of tasks still holds.
Figure 6: GLUE task accuracy comparison (higher is better) after two fine-tuning epochs of grid-search based and the proposed GP-TS based pre-trained models.