A Simple Dynamic Bandit Algorithm for Hyper-parameter Tuning

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Problem and Objectives

We treat the **hyper-parameter tuning** problem for *supervised learning* tasks.

- global optimisation task: $\min\{f(\boldsymbol{\lambda}) : \boldsymbol{\lambda} \in \Omega\}$;
- $f(\boldsymbol{\lambda}) \triangleq \mathbb{E}\left[\ell\left(\mathbf{Y}, g_{\boldsymbol{\lambda}}^{(n)}(\mathbf{X})\right)\right]$ measures the generalization power;
- goal: a simple, robust, (almost) parameter-free bandit algorithm.

How and Why

How?

- We see the problem as a *stochastic infinitely many-armed bandit*
- Beta-Bernoulli bandit model
- A Beta resevoir ν_0 over the means of the arms
- A uniform prior Π_0 over the arms → posterior:

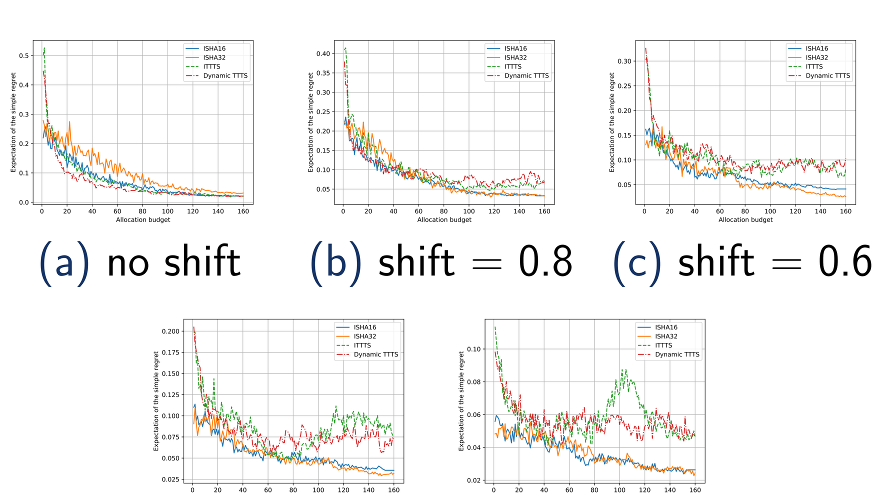
$$\Pi_t = \overset{k_t}{\underset{i=1}{\otimes}} \texttt{Beta}(1 + S_{t,i}, N_{t,i} - S_{t,i} + 1)$$

- At each round, D-TTTS either **samples a new arm** or **re-samples a previous one**, and runs TTTS on the increasing set of arms

Why?

→ TTTS is *anytime* for finitely-armed bandits
→ The number of arms added by D-TTTS depends on the difficulty of the task (the resevoir)
→ e.g. if the resevoir is difficult (like Beta(5,1)), the pseudo-arm μ_0 will be sampled more often
→ D-TTTS **does not** need to fix the number of arms sampled in advance, and naturally **adapts** to the difficulty of the task

When it fails? ← If $\mu^\star \neq 1$?



(a) no shift (b) shift = 0.8 (c) shift = 0.6 (d) shift = 0.4 (e) shift = 0.2

Notation and Glossary

- Ω is the hyper-parameter space
- $\boldsymbol{\lambda}$ is a hyper-parameter configuration
- $g_{\boldsymbol{\lambda}}$ is a classifier
- ℓ is the cross-validation error in this work
- $\mu_1, \mu_2, \cdots$ denote the true means
- Θ is the parameter space
- $\Theta_i \triangleq \{\boldsymbol{\theta} \in \Theta \,|\, \theta_i > \max_{j \neq i} \theta_j\}$ is the subset of arm i being optimal

Recommendation Rule

We recommend the arm with the largest *posterior probability of being optimal*:

$$\bar{I}_n \triangleq \underset{i \in \mathcal{A}}{\arg\max}\, \Pi_n(\Theta_i).$$

Sampling Rule

```
Input: β
Initialization: μ_1 ~ ν_0; A = {μ_1}; m = 1; S_1, N_1 = 0
while budget still available do
  μ_{m+1} ~ ν_0; A ← A ∪ {μ_{m+1}}
  S_{m+1}, N_{m+1} ← 0; m ← m + 1
  ∀i ∈ A, θ_i ~ Beta(S_i + 1, N_i − S_i + 1)
  I^(1) = arg max_{i=0,...,m} θ_i
  if U(~ U([0,1])) > β then
   while I^(2) ≠ I^(1) do
    ∀i ∈ A, θ'_i ~ Beta(S_i + 1, N_i − S_i + 1)
    I^(2) ← arg max_{i=0,...,m} θ'_i
   end while
   I^(1) ← I^(2)
  end if
  Y ← evaluate arm I^(1); X ~ Ber(Y)
  S_{I^(1)} ← S_{I^(1)} + X; N_{I^(1)} ← N_{I^(1)} + 1
end while
```

Some Tricks

- Binarization trick: When a reward $Y_{t,i} \in [0,1]$ is observed, the algorithm is updated with a fake reward $Y'_{t,i} \sim \texttt{Ber}(Y_{t,i}) \in \{0,1\}$.
- Order statistic trick: At time t, let $\mathcal{L}_{t-1}$ be the list of arms that have been efficiently sampled, we run TTTS on the set $\mathcal{L}_{t-1} \cup \{\mu_0\}$ where μ_0 is a pseudo-arm with posterior distribution $\texttt{Beta}(t - |\mathcal{L}_{t-1}|, 1)$.

Experimental Setting

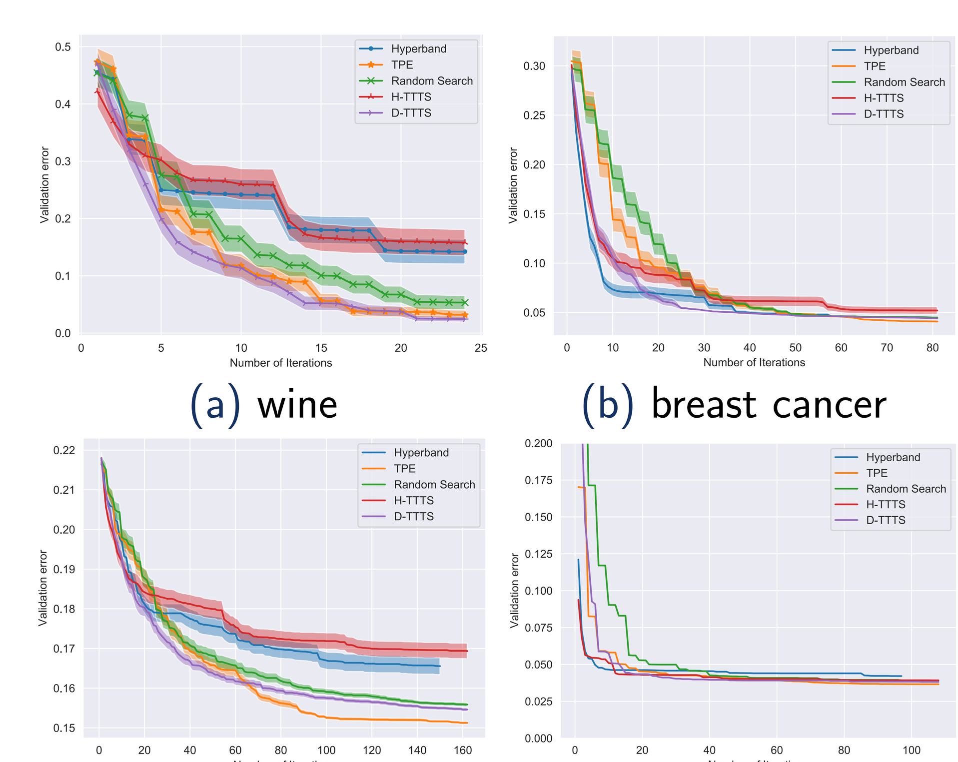
Classifier	Hyper-parameter	Type	Bounds
SVM	C	$\mathbb{R}^+$	$[10^{-5}, 10^5]$
	γ	$\mathbb{R}^+$	$[10^{-5}, 10^5]$

Table: hyper-parameters to be tuned for UCI experiments.

Classifier	Hyper-parameter	Type	Bounds
MLP	hidden_layer_size	Integer	$[5, 50]$
	alpha	$\mathbb{R}^+$	$[0, 0.9]$
	learning_rate_init	$\mathbb{R}^+$	$[10^{-5}, 10^{-1}]$

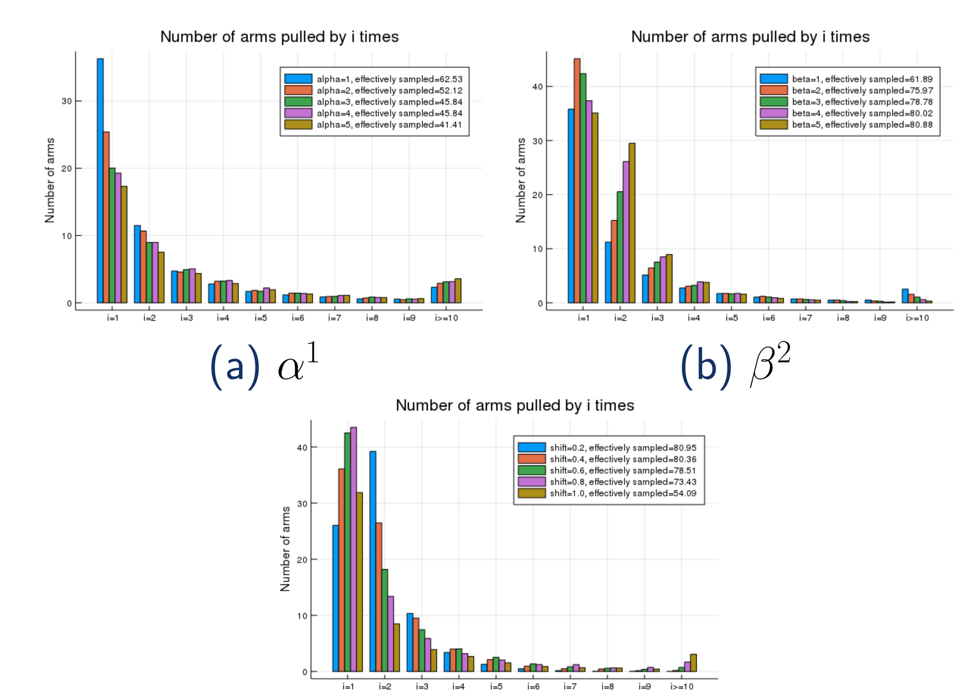
Table: hyper-parameters to be tuned for MNIST experiments.

Results for HPO



(a) wine (b) breast cancer (c) adult (d) MNIST

Illustrations of Efficiently Sampled Arms



(a) α^1 (b) β^2 (c) shift[3]

1. efficiently sampled arms for $\texttt{Beta}(\alpha, 1)$ resevoirs
2. efficiently sampled arms for $\texttt{Beta}(1, \beta)$ resevoirs
3. efficiently sampled arms for shifted Beta resevoirs

References

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Acknowledgements

The research presented was supported by European CHIST-ERA project DELTA, French Ministry of Higher Education and Research, Nord-Pas-de-Calais Regional Council, Inria and Otto-von-Guericke-UniversitÃdt Magdeburg associated-team north-European project Allocate, and French National Research Agency projects BADASS (n.ANR-16-CE40-0002), and BoB (n.ANR-16-CE23-0003).