JOHNS HOPKINS
WHITING SCHOOL of ENGINEERING

CLSP Seminar

Feb 28. 2020

JOHNS HOPKINS
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Speaker 1

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Hyperparameter Optimization of Neural Machine Translation Systems

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Overview

0. Introduction to Hyperparameter Optimization (HPO)

I. A new benchmarking dataset for HPO of NMT systems

II. A new HPO method

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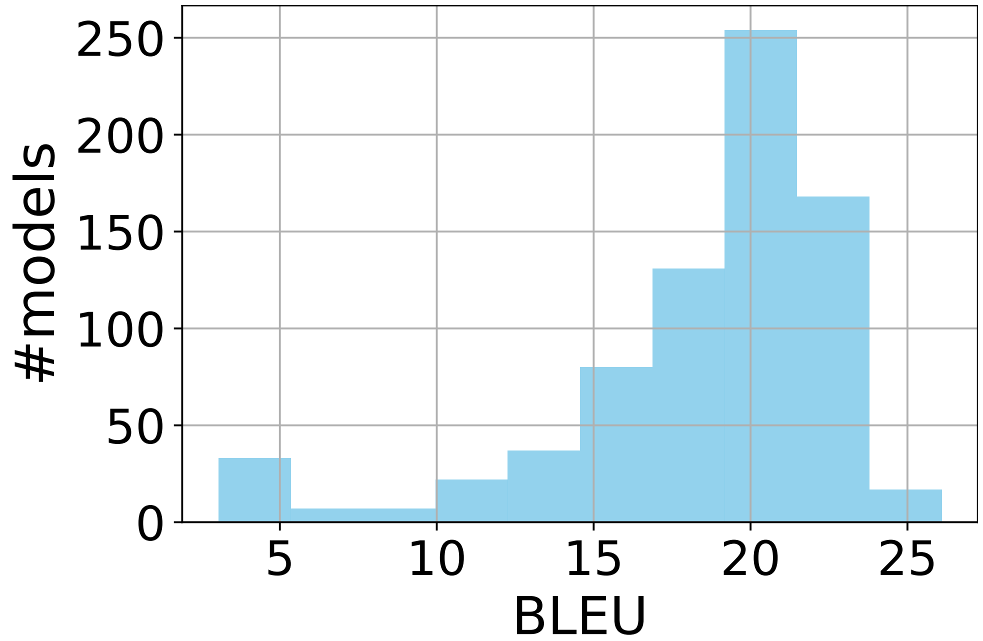
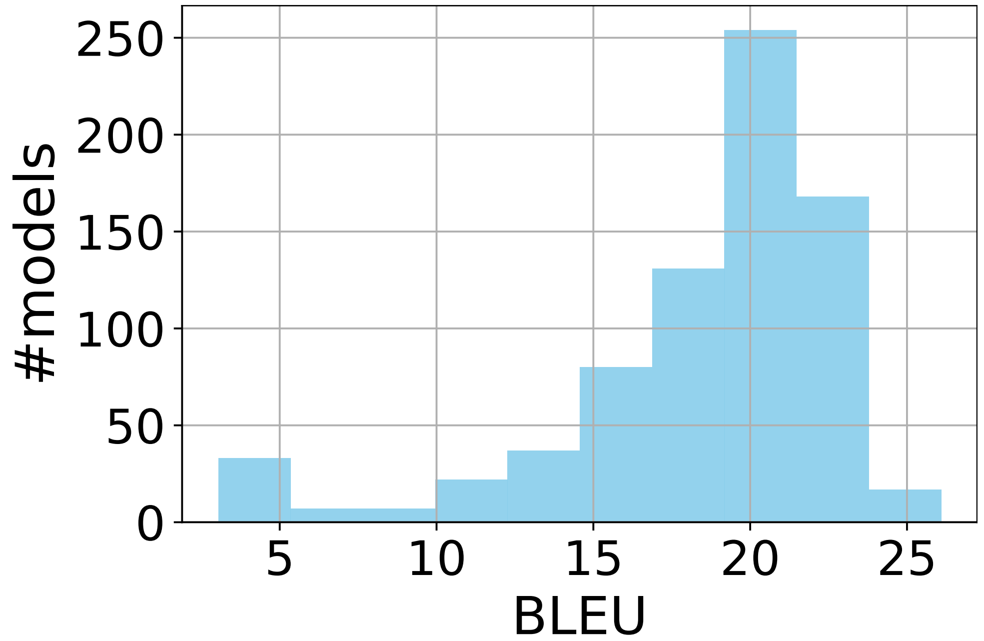
0. Hyperparameter Optimization - Motivation

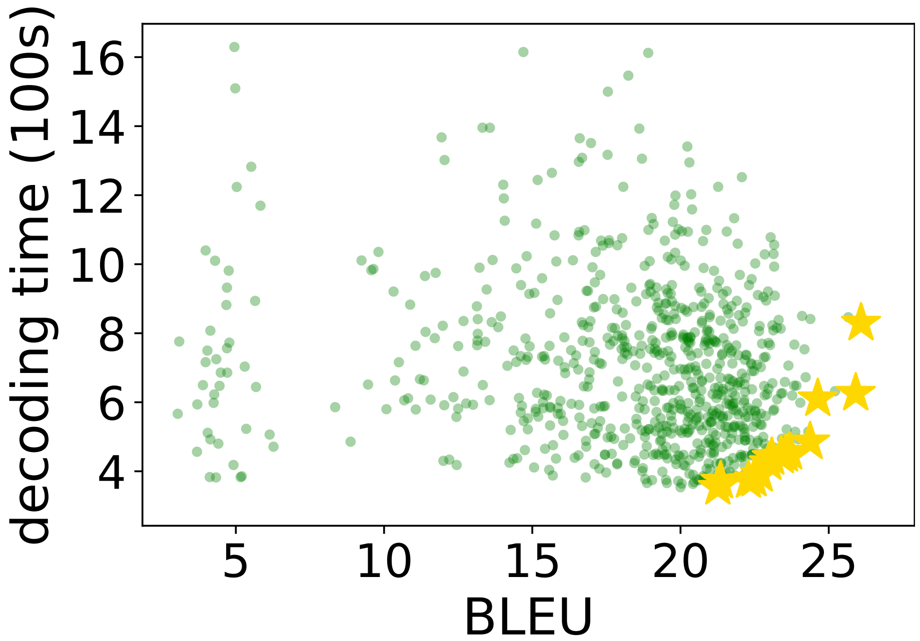
- Choosing effective hyperparameters is crucial for building strong NMT systems: *initial learning rate, batch size, etc.*



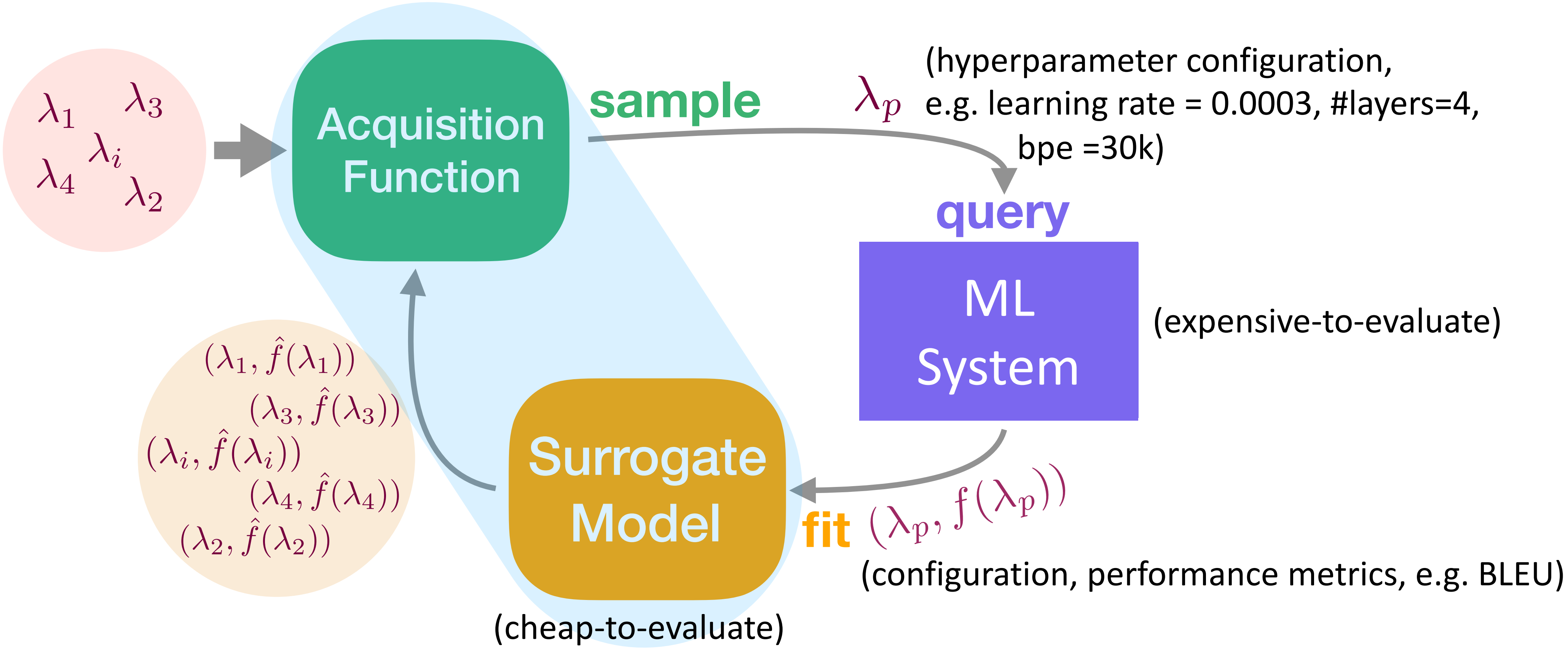
0. Hyperparameter Optimization - Motivation

- Choosing effective hyperparameters is crucial for building strong NMT systems: *initial learning rate, batch size, etc.*
- Manual tuning is tedious and unreliable, especially when optimizing multiple objectives: *BLEU & decoding time.*





0. Hyperparameter Optimization - Approach



Goal: find a hyperparameter configuration $\boldsymbol{\lambda}_\star = \arg\min_{\boldsymbol{\lambda} \in \boldsymbol{\Lambda}} f(\boldsymbol{\lambda})$ with as few evaluations of $f(\cdot)$ as possible.

0. Hyperparameter Optimization - Challenges

- State-of-the-art NMT models require significant **computational resources** for training.

- NMT models usually have large hyperparameter **search space**.

-> It is expensive to compare HPO methods on NMT tasks.

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I. Table-Lookup Datasets for NMT HPO

- First, we pretrain a large number of NMT systems covering a wide range of hyperparameter configurations, and record their performance metrics.
- Then, we constrain our HPO methods to sample from this finite set of models.

I. Table-Lookup Datasets for NMT HPO

- **MT Data:**
  Ted talks: **zh-en, ru-en**; WMT: **ja-en, en-ja**; low-resource: **sw-en, so-en**

- **Model:** Transformer

- **Hyperparameters:**
  preprocessing configurations: bpe
  training settings: initial learning rate
  architecture designs: #layers, embed, #hidden, #heads in self-attention

- **Objectives:**
  translation accuracy: dev BLEU, dev perplexity
  computational cost: decoding time, training time, GPU memory for training, total number of model parameters

I. Table-Lookup Datasets for NMT HPO

dataset	**bpe** (1k)	**#layers**	**#embed**	**#hidden**	**#att_heads**	**init_lr** (10^{-4})
zh, ru, ja, en	10, 30, 50	2, 4	256, 512, 1024	1024, 2048	8, 16	3, 6, 10
sw	1, 2, 4, 8, 16, 32	1, 2, 4, 6	256, 512, 1024	1024, 2048	8, 16	3, 6, 10
so	1, 2, 4, 8, 16, 32	1, 2, 4	256, 512, 1024	1024, 2048	8, 16	3, 6, 10

Table 1: Hyperparameter search space for the NMT systems.

Dataset	**#models**	**Best BLEU**	**bpe**	**#layers**	**#embed**	**#hidden**	**#att_heads**	**init_lr**
zh-en	118	14.66	30k	4	512	1024	16	3e-4
ru-en	176	20.23	10k	4	256	2048	8	3e-4
ja-en	150	16.41	30k	4	512	2048	8	3e-4
en-ja	168	20.74	10k	4	1024	2048	8	3e-4
sw-en	767	26.09	1k	2	256	1024	8	6e-4
so-en	604	11.23	8k	2	512	1024	8	3e-4

Table 2: For each language pair, we report the number of NMT systems trained on it, the oracle best BLEU we obtained and its corresponding hyperparameter configuration.

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II. Graph-Based Semi-Supervised Learning as a HPO Method

- **Semi-supervised learning:** utilize a handful of labeled data and a large amount of unlabeled data to improve prediction accuracy.

- **Graph-Based Semi-Supervised Learning (Zhu et al., 2003):** describes the structure of data with a graph.

vertex: (data point, label) → (configuration, model performance)
edge weight: similarity between vertices → similarity between configurations
smoothness: neighbors connected by edges tend to have similar labels.
Predict: Labels can propagate throughout the graph.