ML4AAD - Final Project

Winter Semeseter 18/19

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4774378

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Motivation (The Why)

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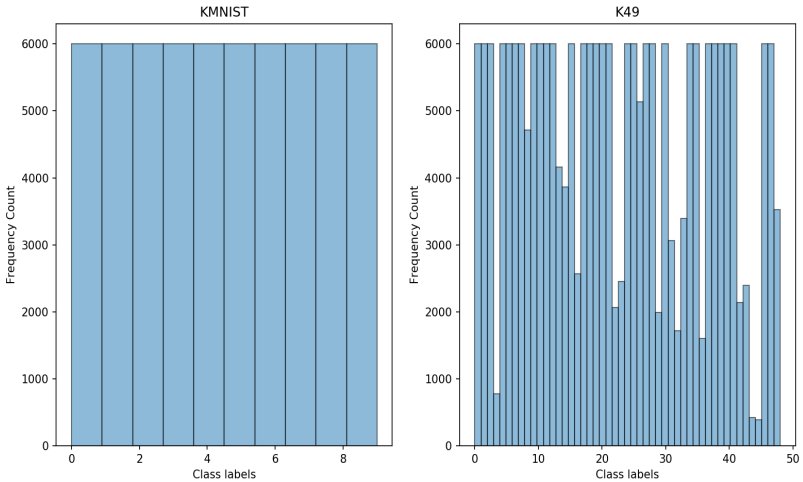
2 (similar) datasets with differing size, # of classes, class balance



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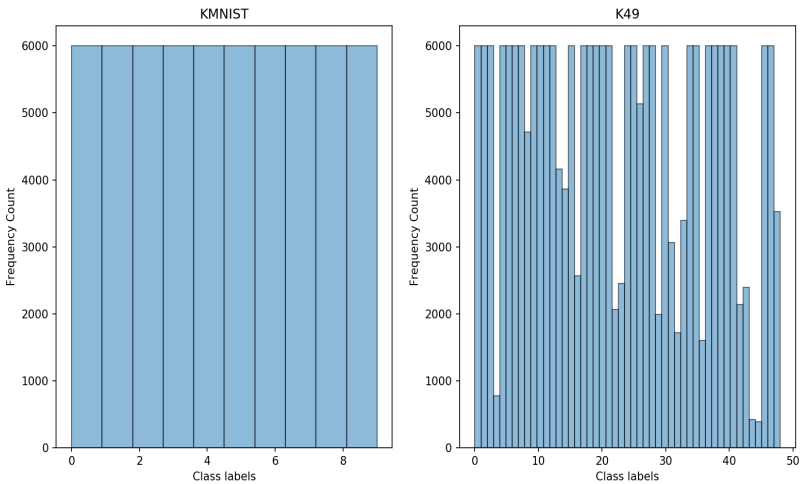
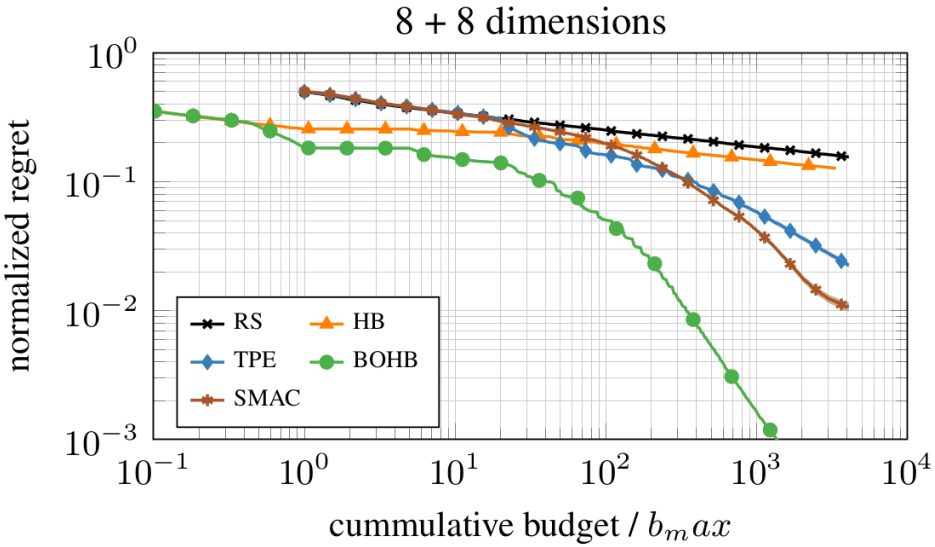


BOHB outperforms SMAC in high dimensional, mixed data



Design Decisions (and BOHB)

CNN Structure

$INPUT \rightarrow [CONV \rightarrow BATCHNORM? \rightarrow ACTIVATION \rightarrow DROPOUT? \rightarrow MAXPOOL?]*M \rightarrow [FC \rightarrow BATCHNORM? \rightarrow ACTIVATION \rightarrow DROPOUT?]*K \rightarrow OUTPUT$

$M \in \{1, 2, 3\}$; $K \in \{0, 1, 2\}$; $? \rightarrow \top or \bot$

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- CONVolution layers
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  - Padding
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- BATCHNORM, DROPOUT
  - True or False
- MAXPOOL (if True)
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- >30 hyperparameters
- (Budget = Epochs) $\rightarrow$ expensive runs

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BOHB params:

eta	min_budget	max_budget
2	1	16
4	1	16
3	1	9
2	1	10

BOHB on KMNIST (and K49)

Dataset	eta_min_max_iter (BOHB)	Validation Accuracy	Train Accuracy	Test Accuracy	BOHB Runtime
KMNIST	2_1_16_10	98.08%	99.81%	95.06%	<3 hrs
KMNIST	3_1_9_20	97.17%	98.23%	93.26%	<3 hrs
KMNIST	4_1_16_20	98.26%	99.98%	96.41%	<4 hrs
KMNIST	2_1_10_14	97.77%	99.86%	94.08%	<4 hrs
KMNIST	3_2_20_20	98.31%	99.62%	95.41%	<6 hrs

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K49	3_1_9_10	89.06%	99.93%	88.12%	<5 hrs
K49	2_1_10_10	91.19%	99.25%	88.25%	<12 hrs

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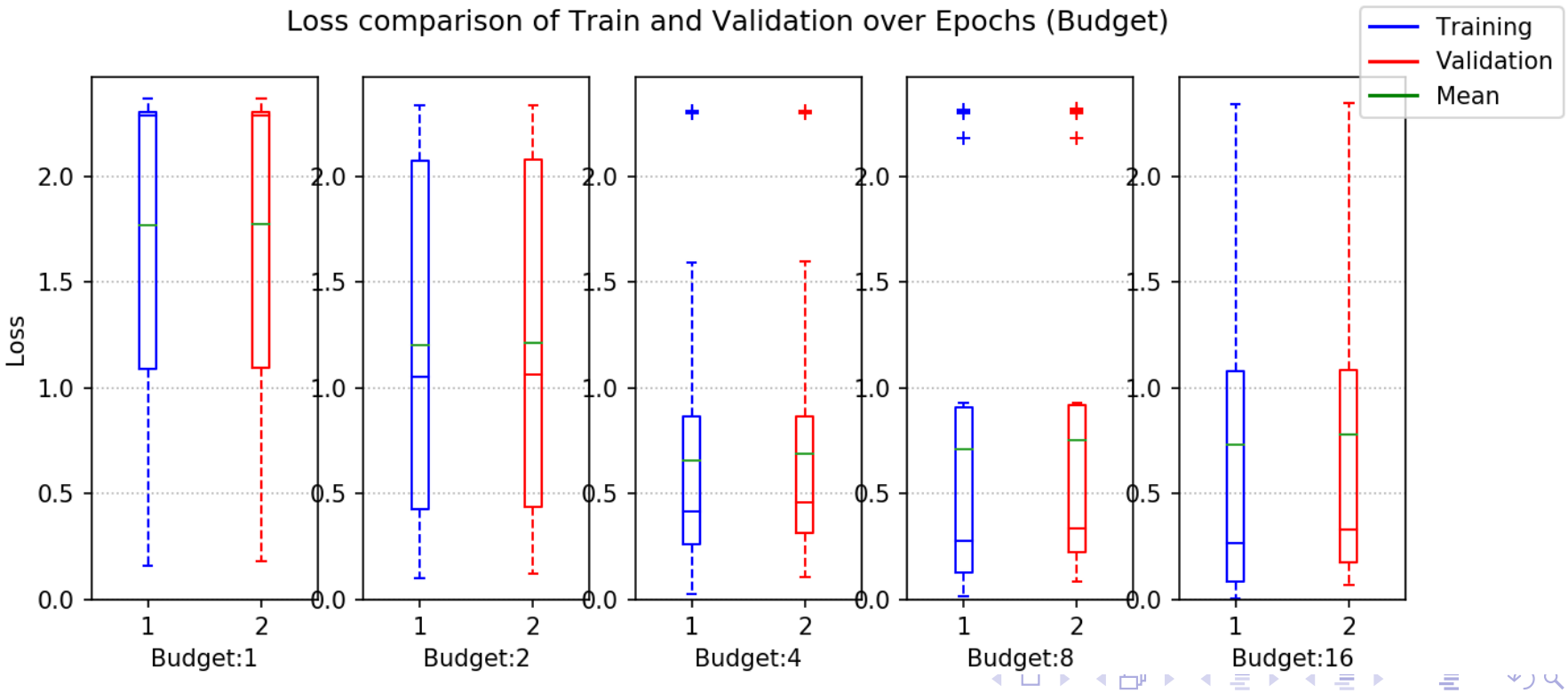

Extracting juice (Can K49 leverage KMNIST?)

Model: KMNIST $\rightarrow$ K49

KMNIST Test	K49 Train	K49 Test	Run-time
95.06%	97.15%	90.49%	<2hrs
95.41%	95.91%	90.63%	<1hr
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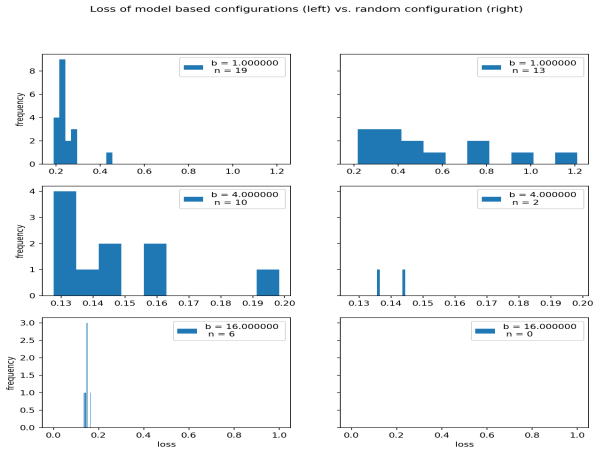

Configuration: KMNIST $\xrightarrow{\text{BOHB}}$ K49

Hyperparameters:

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- # of FC layers and neurons
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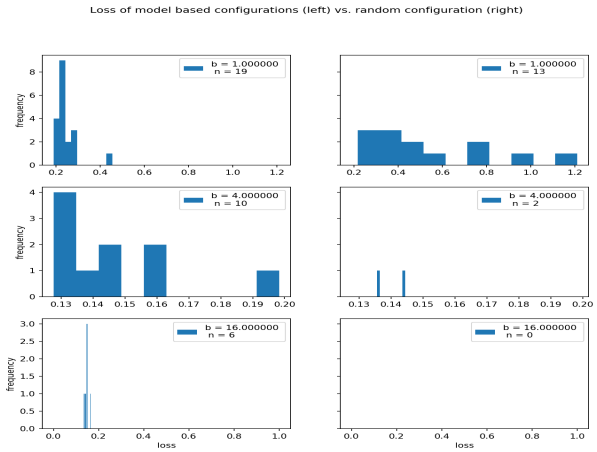

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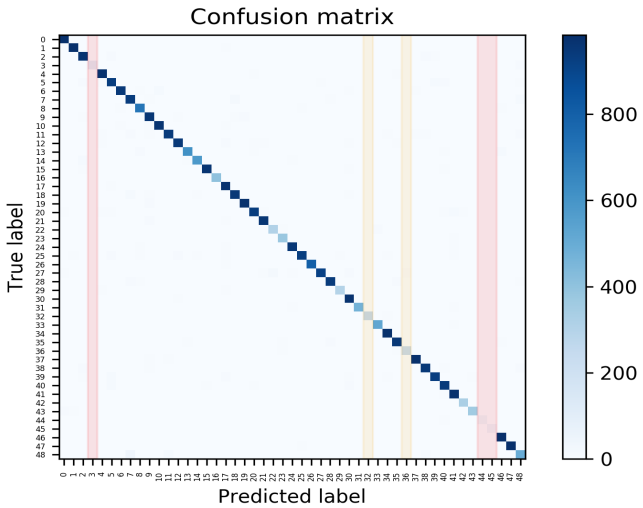

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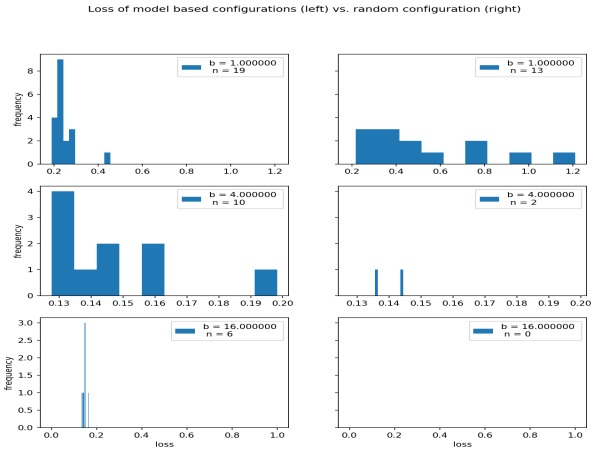

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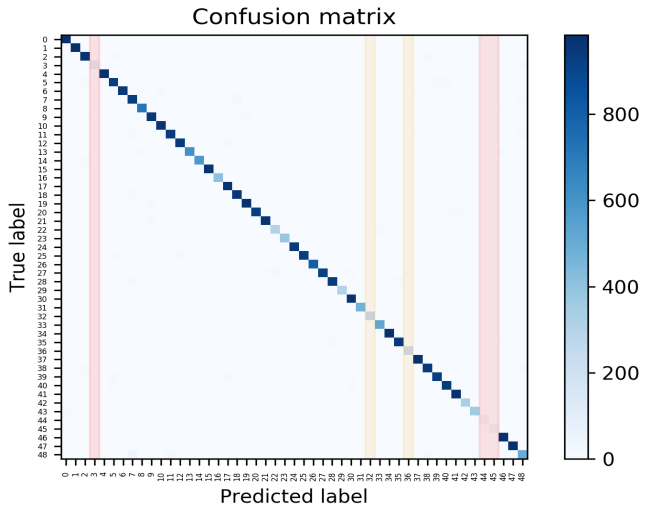

Issues: (i) Under-represented classes; (ii) Slow experiments; [(iii) What if only K49?]

In Conclusion...

Possible improvements:

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- NAS cell search
- Padding to go deeper (exploit sparsity)

Final Numbers:

Dataset	Default Test	Best Test
KMNIST	69.56%	97.89%
K49	54.43%	94.28%

KMNIST: *from transferring best K49 model*
K49: *from transferring incumbent config on KMNIST and then BOHB on K49*