## HYPERPARAMETER OPTIMIZATION

MODEL UNCERTAINTY IN MACHINE LEARNING

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## INDUCTIVE BIAS

ASSUMPTIONS OF OUR MODELS



## NO FREE LUNCH

HOW WELL YOU DO IS DETERMINED BY HOW 'ALIGNED' YOUR LEARNING ALGORITHM P(H|D)
IS WITH THE ACTUAL POSTERIOR, P(F|D).
-DAVID H. WOLPERT

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## DEEP LEARNING?

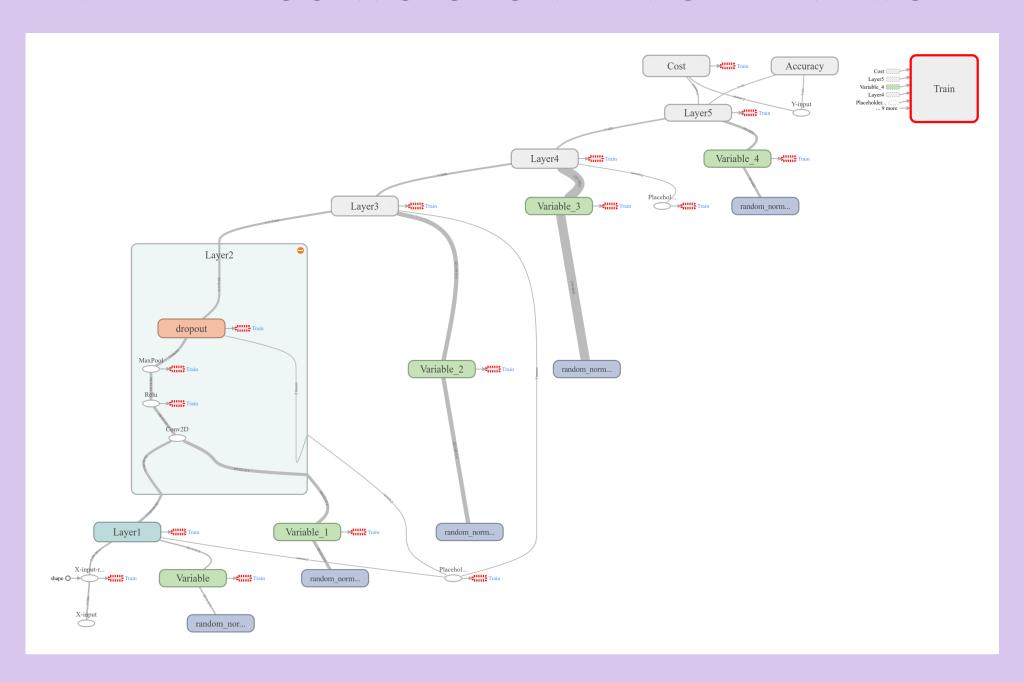
ONLY WITH THE PROPER PARAMETERS

## PARAMETER CHOICES, A DARK ART



Harry Potter and the Half Blood Prince

#### FIVE LAYER CONVOLUTIONAL NEURAL NETWORK



#### **CNN ONE PARAMETERS:**

Learning Rate: 0.1;

Number of Epochs: 8000; Batch Size: 25;

Convolution Layer Dropout: 0.2; Fully Connected Layer Dropout: 0.2

#### **TEST ACCURACY: 0.937**



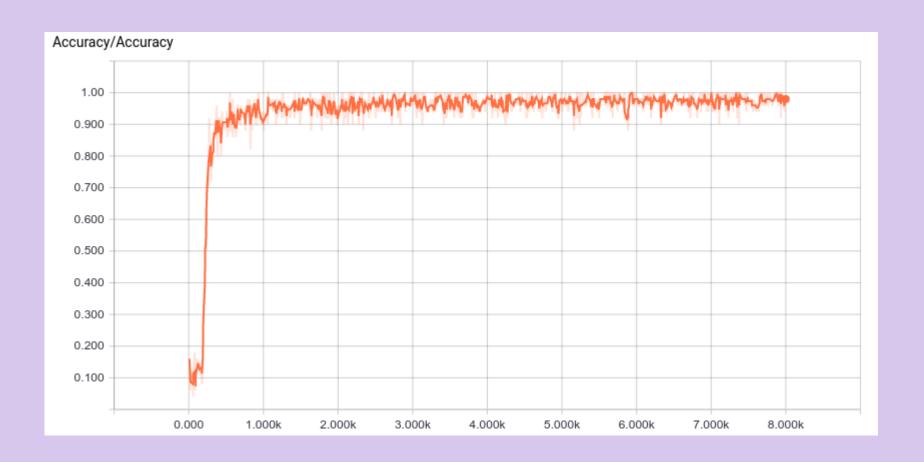
#### **CNN TWO PARAMETERS:**

Learning Rate: 0.01;

Number of Epochs: 8000; Batch Size: 50;

Convolution Layer Dropout: 0.5; Fully Connected Layer Dropout: 0.8

TEST ACCURACY: 0.9896



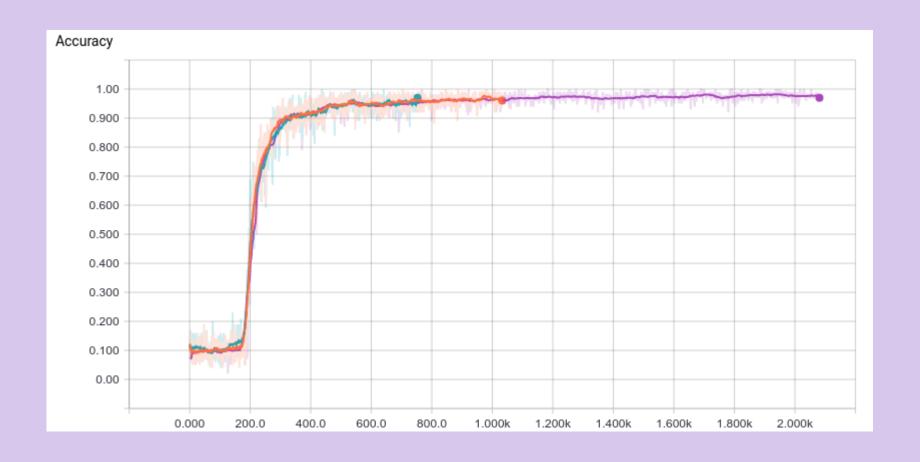
#### **CNN THREE PARAMETERS:**

Learning Rate: 0.001;

Number of Epochs: 8000; Batch Size: 100;

Convolution Layer Dropout: 0.7; Fully Connected Layer Dropout: 0.5

#### **TEST ACCURACY: 0.9925**



## METHODS

FORMALIZING OUR HYPERPARAMETER SEARCH



## RANDOM SEARCH

J BERGSTRA, Y BENGIO 'RANDOM SEARCH FOR HYPER-PARAMETER OPTIMIZATION' - JOURNAL OF MACHINE LEARNING RESEARCH, 2012



# TREE-STRUCTURED PARZEN ESTIMATORS

HYPEROPT

BERGSTRA, JAMES S., ET AL. "ALGORITHMS FOR HYPER-PARAMETER OPTIMIZATION." ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS. 2011.

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## GAUSSIAN PROCESSES

#### SPEARMINT

PRACTICAL BAYESIAN OPTIMIZATION OF MACHINE LEARNING ALGORITHMS
JASPER SNOEK, HUGO LAROCHELLE AND RYAN PRESCOTT ADAMS
ADVANCES IN NEURAL INFORMATION PROCESSING SYSTEMS. 2012

## FUTURE WORK