Learning What Data to Learn

Recent Trends in Automated Machine Learning (AutoML) (IN2107, IN4954)

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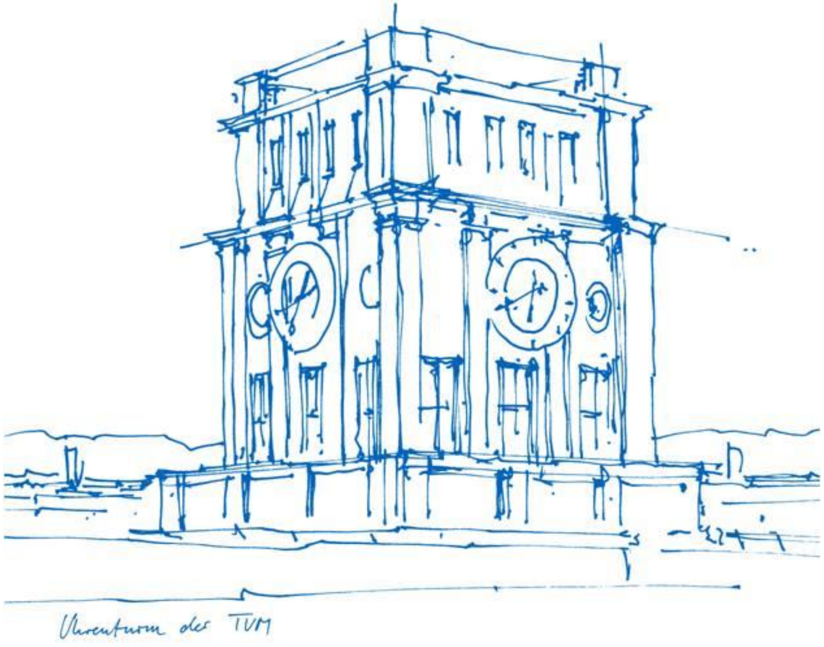


An Adaptive Data Selection Strategy

- Curriculum Learning (CL), *Bengio et al., 2009*
- Self-paced Learning (SPL), *Kumar et al., 2010*

*How do we **automatically and dynamically** allocate appropriate training data at different stages of machine learning?*

An Adaptive Data Selection Strategy

Proposition: Two-fold intuitive principles!

The data selection strategy should be:

- General enough
- Forward-looking

The teacher-student framework

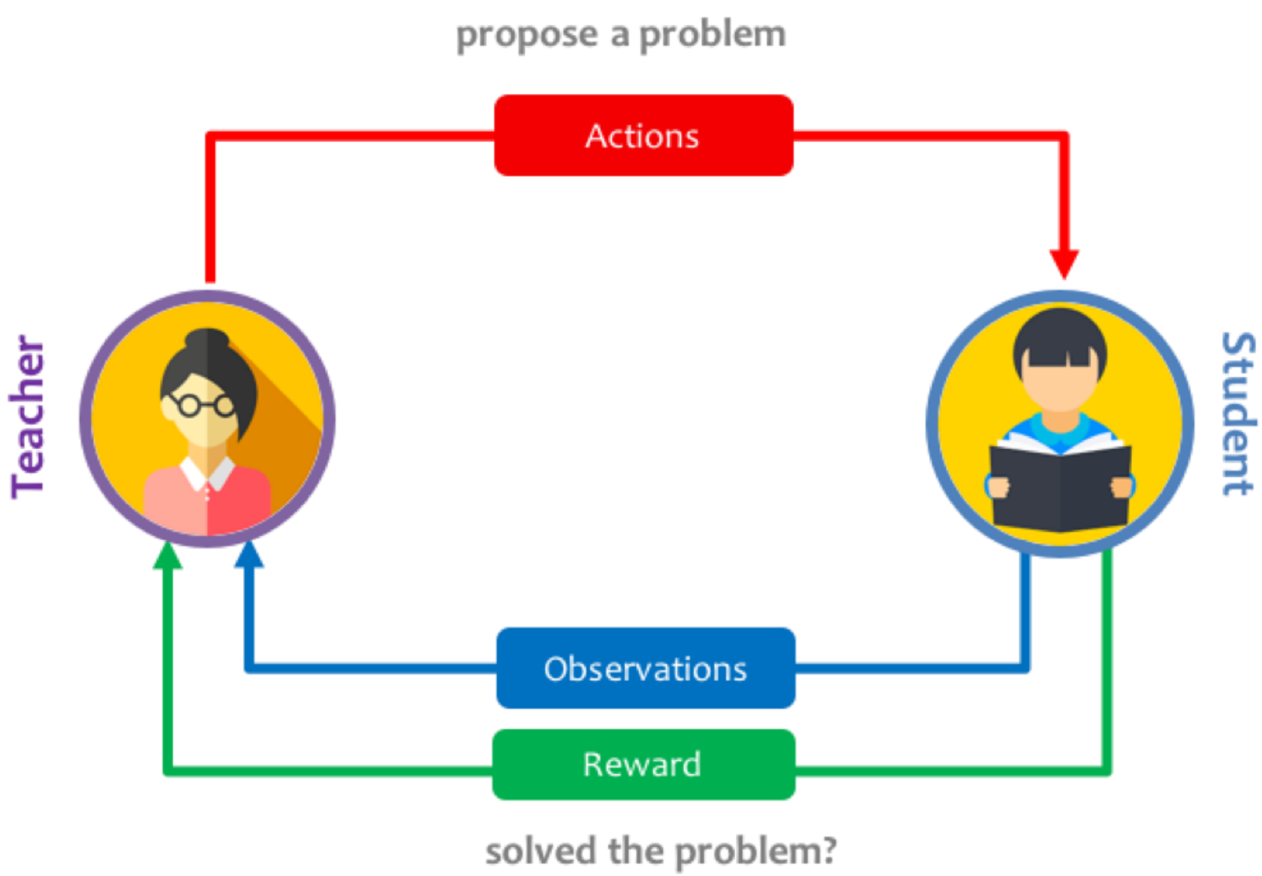
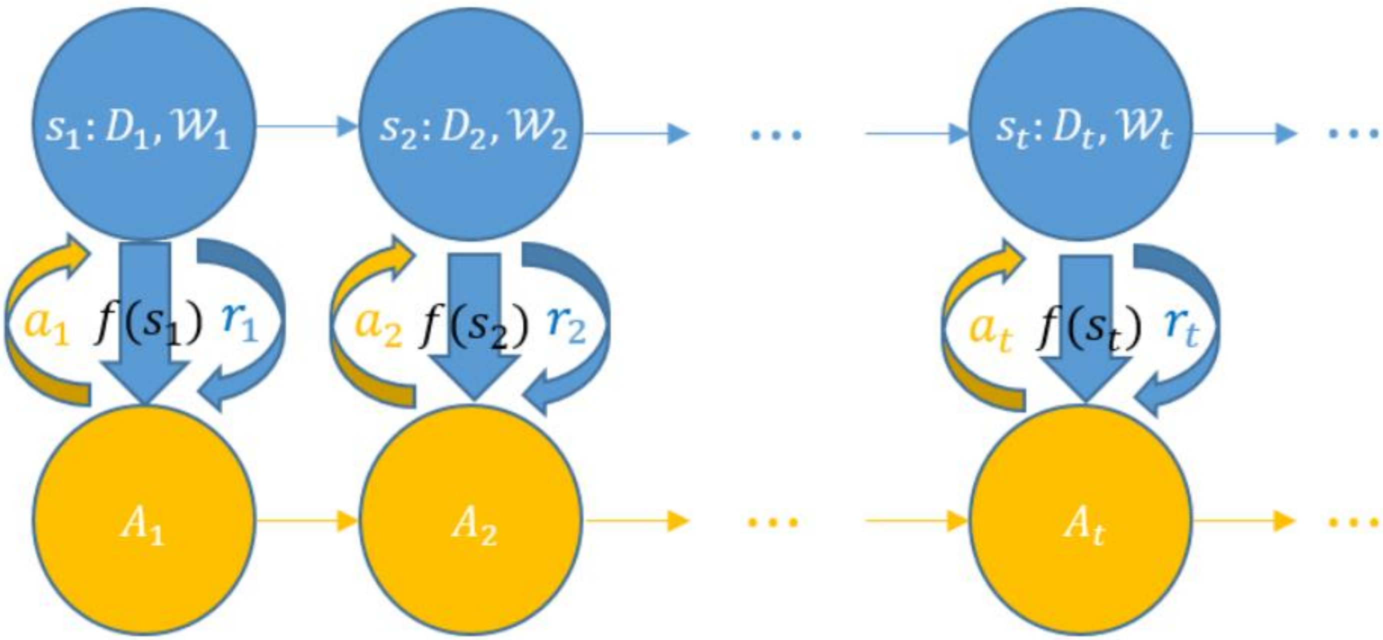


Figure credit: https://rlcurriculum.github.io/

Neural Data Filter (NDF)

- Deep Reinforcement Learning to determine whether/how to filter the given mini-batch of training data.
- The SGD training for the base Machine Learning model is casted into a Markov Decision Process (MDP).

The structure of SGD accompanied with NDF



NDF: Definition

SGD-MDP: $< s, a, \mathcal{P}, r, \gamma >$

- s is the state, $s_t = (D_t, \mathcal{W}_t)$.
- a is the action space.
  - For data filtration task, we have: $a = \{a_m\}_{m=1}^{M} \in \{0,1\}^M$.
- $\mathcal{P}_{ss'}^{a} = P(s'|s,a)$ is the state transition probability.
- $r = r(s,a)$ is the reward.
- $\gamma \in [0,1]$ is the discount factor.

NDF: Definition

SGD-MDP: $< s, a, \mathcal{P}, r, \gamma >$

- NDF samples the action by its policy function $A = P_{\Theta}(a|s)$ with parameters Θ to be learnt.
- The policy A can be any binary classification model, such as logistic regression.

NDF: State Features

- The aim of designing state feature vector is to ***effectively and efficiently*** represent **SGD-MDP** state.
- Adopt 3 categories features to compose $f(s)$:
  - Data features
  - Base model features
  - Features to represent the combination of both data and model

Algorithm 1: SGD Training with NDF

Algorithm 1 SGD Training with Neural Data Filter.

Input: Training data D.
1. Randomly sample a subset of NDF training data D' from D.
2. Optimize NDF policy network $A(s;\Theta)$ based on D' by policy gradient (details in Algorithm 2).
3. Apply $A(s;\Theta)$ to full dataset D to train the base machine learning model by SGD.

Output: The base machine learning model.

Training Algorithm for NDF Policy

We aim to optimize the following expected reward:

$$J(\Theta) = E_{P_\Theta(a|s)}[R(s,a)]$$

$$\nabla_\Theta = \sum_{t=1}^{T} E_{P_\Theta(a_{1:T}|s)}[\nabla_\Theta \log P(a_t|s_t) R(s_t, a_t)]$$

Which is empirically estimated as:

★ $P_\Theta(a|s)$: $v_t = r_t + \gamma r_{t+1} + \cdots + \gamma^{T-t} r_T$

$$\sum_{t=1}^{T} \nabla_\Theta \log P(a_t|s_t) v_t.$$

Algorithm 2: Train NDF policy

Algorithm 2 Train NDF policy.

Input: Training data D'. Episode number L. Mini-batch size M. Discount factor $\gamma \in [0, 1]$.
Randomly split D' into two disjoint subsets: D'_{train} and D'_{dev}.
Initialize NDF data filtration policy $A(s, a; \Theta)$, i.e., $P_\Theta(a|s)$.

for each episode $l = 1, 2, \cdots, L$ **do**
  Initialize the base machine learning model.
  Shuffle D'_{train} to get the mini-batches sequence $\{D_1, D_2, \cdots\}$.
  $T = 0$.
  while stopping criteria is not met **do**
    $T = T + 1$.
    Sample data filtration action for each data instance in $D_T = \{d_1, \cdots, d_M\}$: $a = \{a_m\}_{m=1}^M$, $a_m \propto P_\Theta(a|s_m)$, s_m is the state corresponding to d_m.
    Update base machine learning model by Gradient Descent based on the selected data in D_T.
    Receive reward r_T computed on D'_{dev}.
  end while
  for $t = 1, \cdots, T$ **do**
    Compute cumulative reward $v_t = r_t + \gamma r_{t+1} + \cdots + \gamma^{T-t} r_T$.

$$\Theta \leftarrow \Theta + \alpha v_t \sum_m \frac{\partial \log P_\Theta(a_m|s_m)}{\partial \Theta} \quad (5)$$

  end for
end for

Output: The NDF policy $A(s, a; \Theta)$.

The experiments

- Unfiltered SGD
- Self-paced Learning (SPL)
- NDF

$$\Theta \leftarrow \Theta + \alpha(r_t - b_l) \sum_m \frac{\partial \log P_\Theta(a|s_m)}{\partial \Theta}.$$

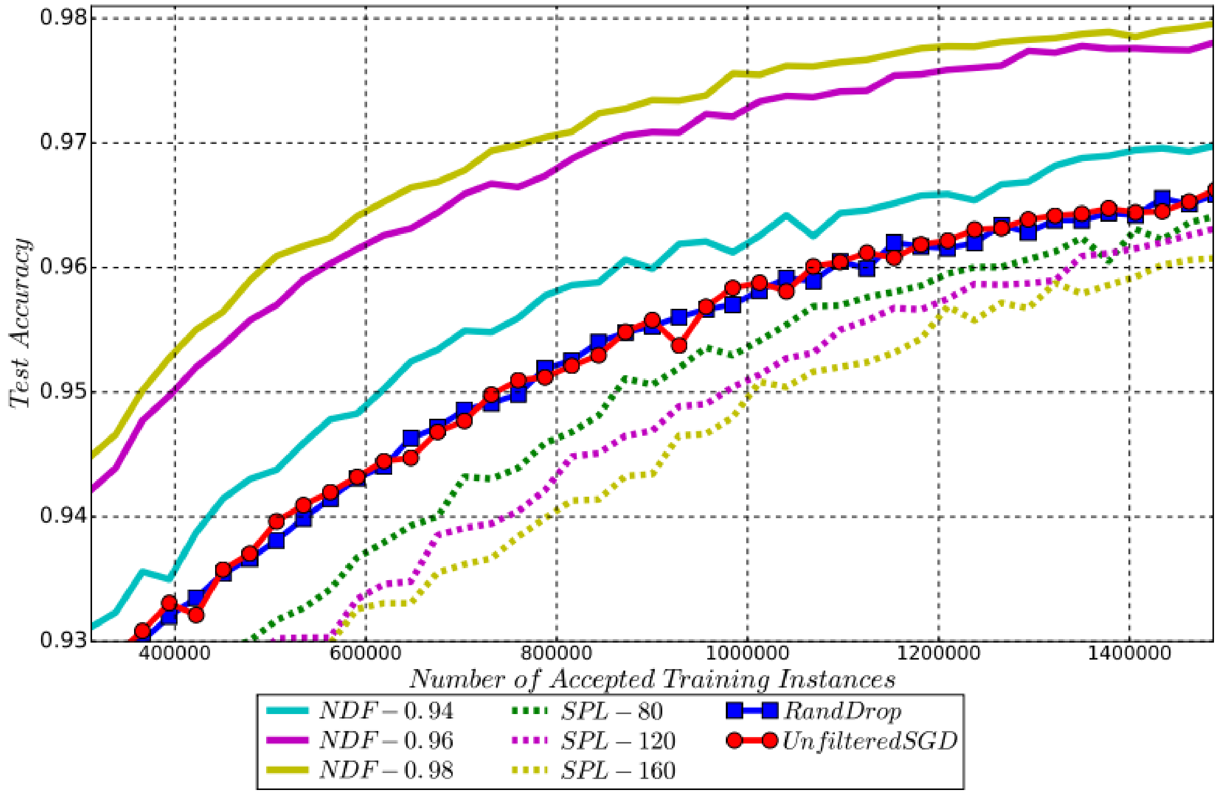
, with the reward baseline b_l for episode l , computed as $b_l = 0.8 b_{l-1} + 0.2 r_l, b_0 = 0$. and v_t is computed as $v_t = r_l$.

- RandDrop

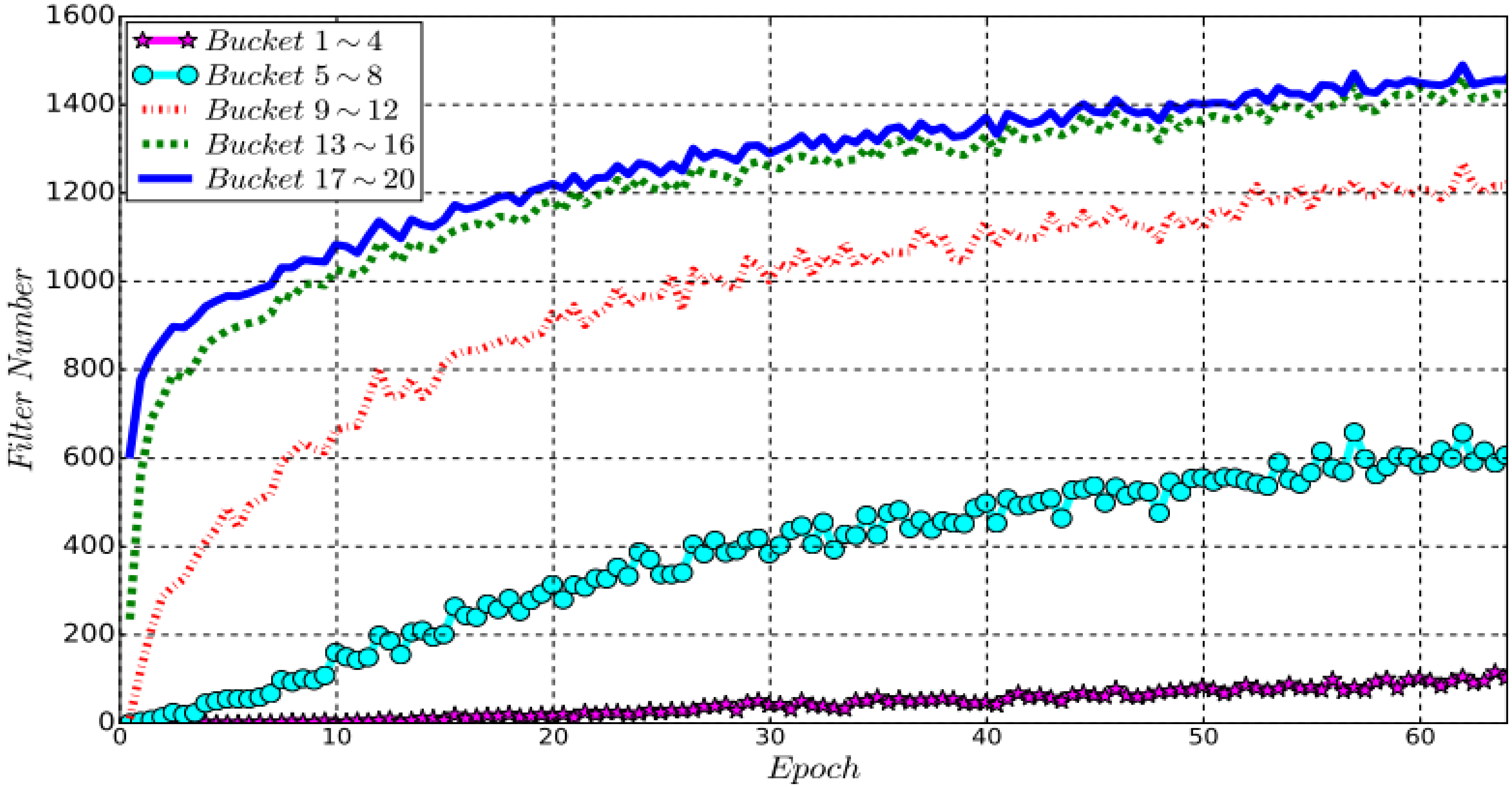
MLP for MNIST

- 60k training and 10k testing images
- **Optimizer:** Momentum-SGD (Mini-batch size = 20).
- **Layer structure:** A 3-layer feedforward neural network with layer size 784 x 500 x 10
- **Loss function:** Cross-entropy
- **L:** 500 Episodes
- **Early Stopping:** Based on validation set accuracy

MLP for MNIST



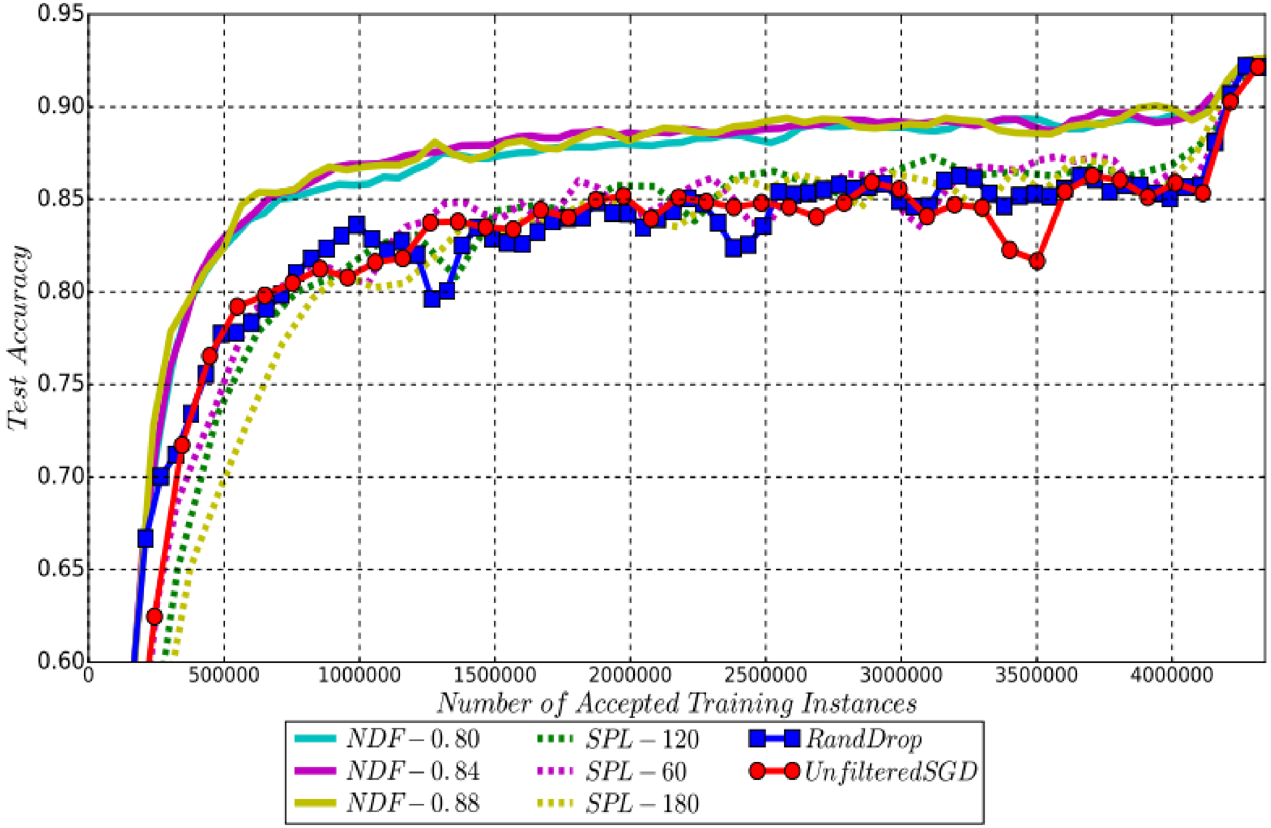
MLP for MNIST



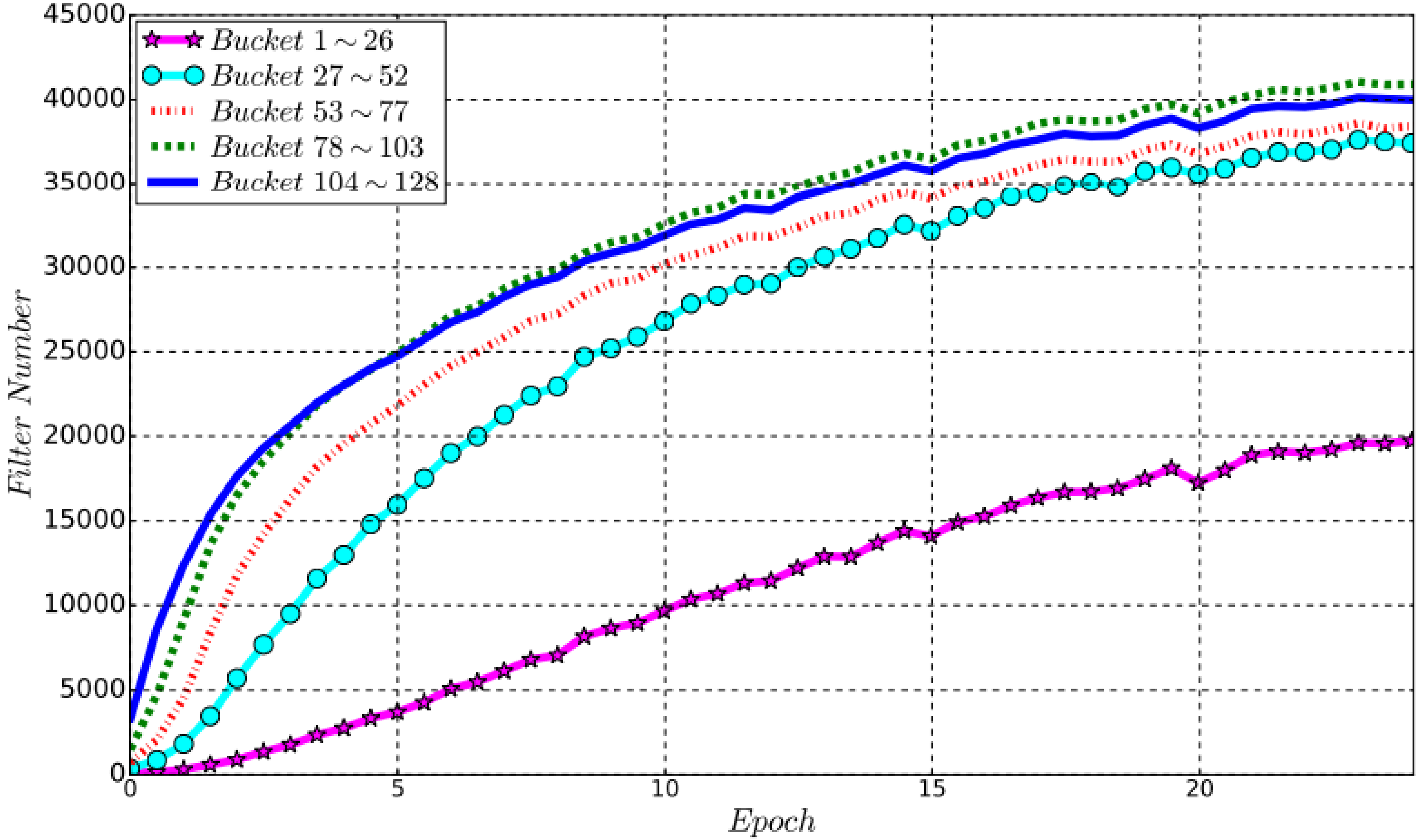
CNN for Cifar10

- 60k RGB images of size 32 x 32 categorized into 10 classes.
- 50k training images and 10k test images.
- **Data Augmentation:** Padding 4 pixels to each side and randomly sampling a 32 x 32 crop.
- **ResNet** is adopted.
- **Optimizer:** Momentum-SGD (Mini-batch size = 128).
- **Learning Rate:** Initially set to 0.1, and multiplied by a factor of 0.1 after the 32k-th and 48k-th model update.
- **L:** 100.

CNN for Cifar10



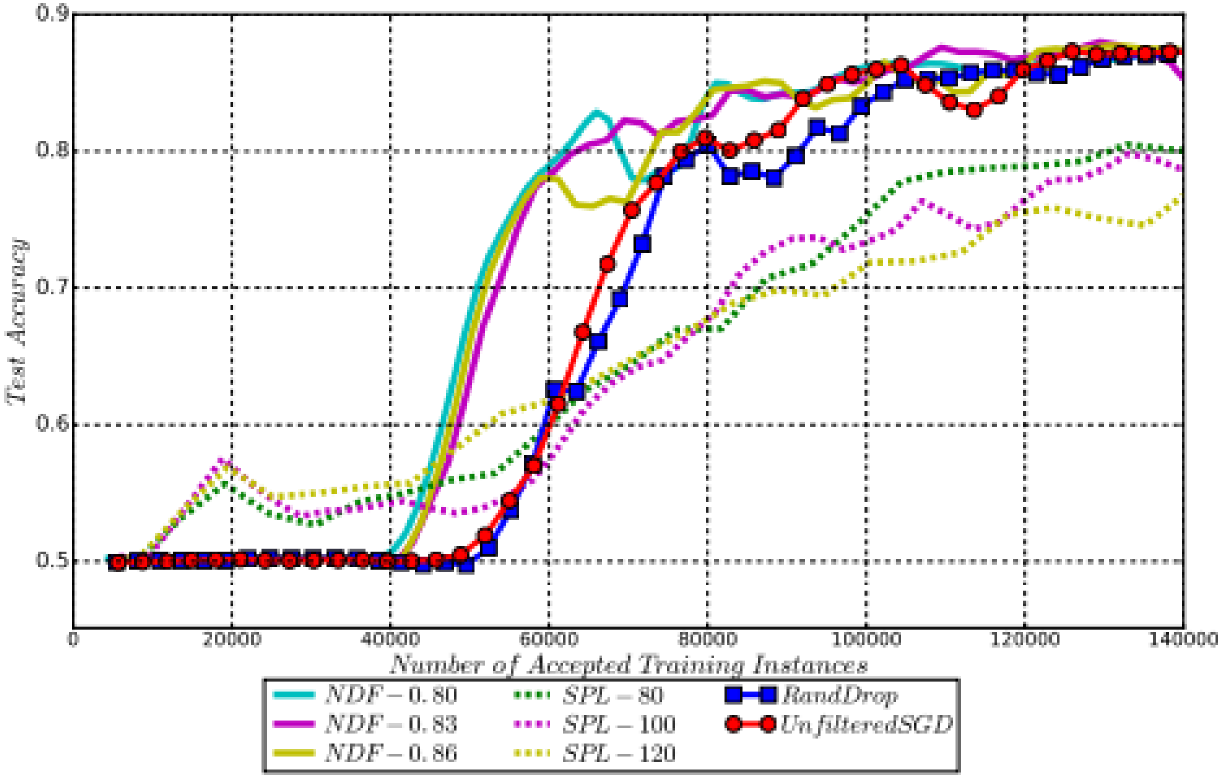
CNN for Cifar10



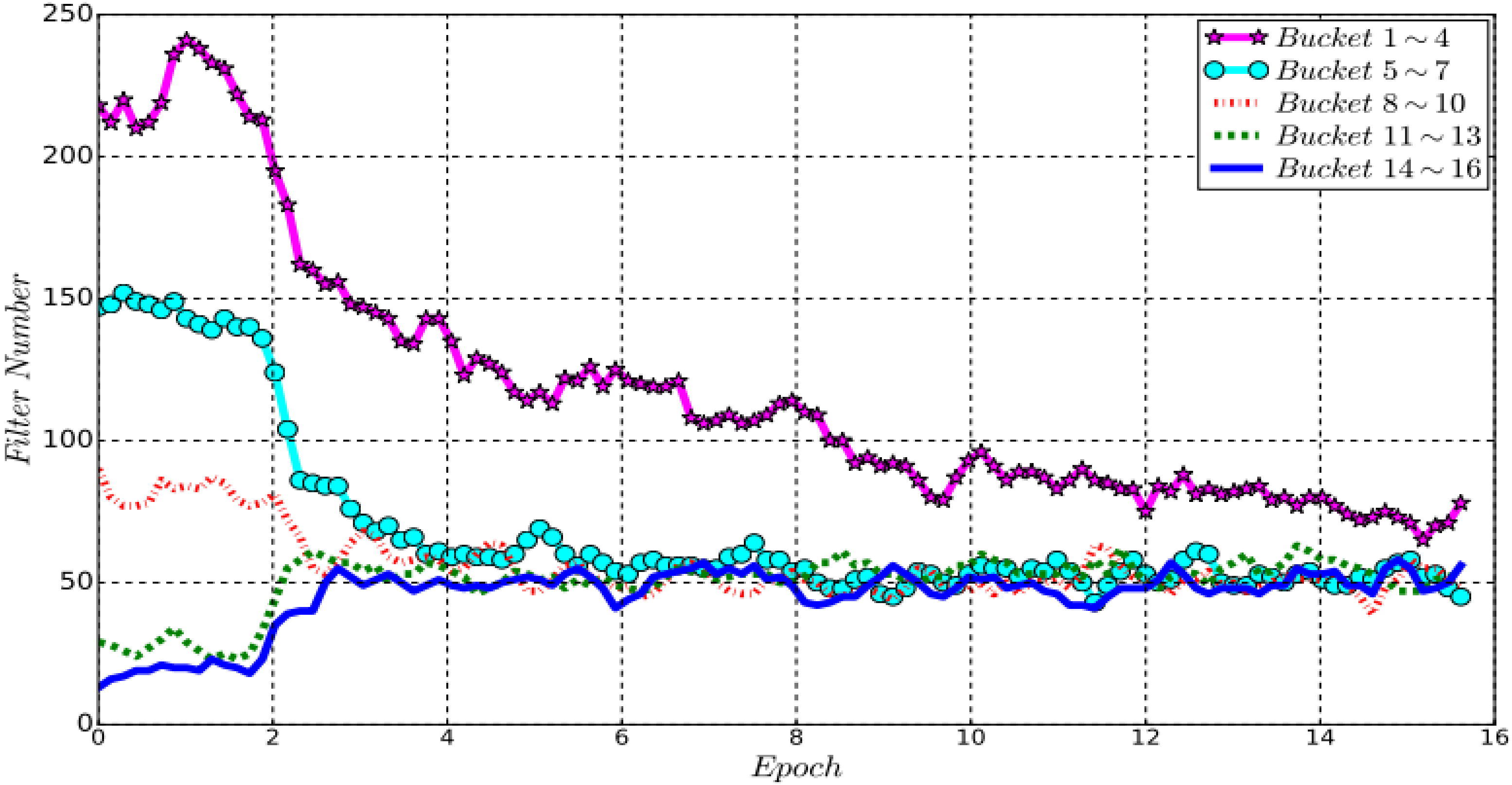
RNN for IMDB sentiment classification

- 50k movie review comments with positive/negative sentiment labels
- 25k training set and 25k test set.
- The size of word embedding in RNN is 256.
- The size of hidden state of RNN is 512.
- Mini-batch size is 16.
- **L:** 200.

RNN for IMDB sentiment classification



RNN for IMDB sentiment classification



Pros

- A good data selection mechanism can effectively accelerate model convergence.
- Different tasks and datasets may favor different data selection policies.
- Not sensitive to the setting of hyper-parameters.

Cons

- For some problems, NDF seems to be indifferent to different setting of hyper-parameters.
- The data selection (hard or easy) matters in some problems.
- Still need to test the algorithm on different scenarios.

Questions???