# Interactive Session: Practical Insights into Deep Learning Optimization


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# Outline

# Brief Overview of Deep Learning

## Deep Learning Paradigms

1. **Supervised Learning**
   - Requires labeled data.
   - Model learns to map input to given label.
   - Examples: image classification, regression, object detection etc.
2. **Self-Supervised Learning**
   - Unlabeled data - can be applied to vast amount of data.
   - Learning algorithm for *Generative Modeling*
   - Examples: *Stable Diffusion, GPTs, Midjourney* etc.
3. **Reinforcement Learning**
   - No explicit labels; learns from reward signals.
   - Model interacts with an environment to maximize cumulative reward.
   - Examples: game playing, robotics etc.

# Yann Lecun's Cake Analogy

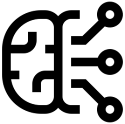
Y. LeCun

## Learning Paradigms: information content per sample

- **"Pure" Reinforcement Learning (cherry)**
  - The machine predicts a scalar reward given once in a while.
  - **A few bits for some samples**
- **Supervised Learning (icing)**
  - The machine predicts a category or a few numbers for each input
  - Predicting human-supplied data
  - **10→10,000 bits per sample**
- **Self-Supervised Learning (cake génoise)**
  - The machine predicts any part of its input for any observed part.
  - Predicts future frames in videos
  - **Millions of bits per sample**

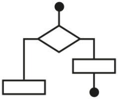
Source: https://leshouches2022.github.io/SLIDES/compressed-yann-1.pdf

# The Pillars of Deep Learning

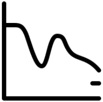


Model

Data



Optimizer



Loss

## Perspectives

- **Mathematics:** ”The model acts like a *universal function approximator* and the data is the *ground truth*.
- **Computer Science:** ”The model acts like a *compiler* and the data is analogous to the *source code*.”

# The Pillars of Deep Learning

Model Data Optimizer Loss

## Perspectives

- **Mathematics:** ”The model acts like a *universal function approximator* and the data is the *ground truth*.
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# Importance of Optimization in Deep Learning

**Risk Minimization:**
Ideal objective: minimize expected loss over true data distribution $p_{\mathrm{data}}$:

$$R(\theta) = \mathbb{E}_{(x,y)\sim p_{\mathrm{data}}}[L(f(x;\theta), y)]$$

**Empirical Risk Minimization:**
Find $\hat{\theta}$ that minimizes the average loss:

$$\hat{\theta} = \arg\min_{\theta} \frac{1}{N} \sum_{i=1}^{N} L(f(x_i;\theta), y_i)$$

**Gradient Descent:**
Iteratively update parameters:

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta \left( \frac{1}{N} \sum_{i=1}^{N} L(f(x_i;\theta_t), y_i) \right)$$

**Mini-Batch Gradient Descent:**
Update using a subset of data:

$$\theta_{t+1} = \theta_t - \eta \nabla_\theta \left( \frac{1}{B} \sum_{i=1}^{B} L(f(x_i;\theta_t), y_i) \right)$$

# Today's Interactive Session

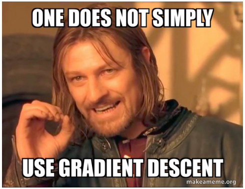
## Goals

1. Understand the foundational concepts in optimization for deep learning.
2. Get hands-on experience in implementing and experimenting with various first-order optimization algorithms in deep learning.
3. Learn about common pitfalls and best practices when optimizing deep learning models.

## Jupyter Notebook:

Repository @ `https://github.com/b-turan/math-plus-summerschool`

If you have any questions, please feel free to contact me. You are invited to discuss your results and insights with the other participants.



# A Leap Forward with Momentum

## Concept of Momentum

- **Basic Idea**: Utilize previous gradients to gain ’momentum’ and speed up convergence.
- **Update Rule**:

$$v_{t+1} = \gamma v_t + \eta \nabla_\theta L(\theta_t)$$

$$\theta_{t+1} = \theta_t - v_{t+1}$$

- **Role of $\gamma$**: Sets the weight of ’memory’ of past gradients. Common value: 0.9.
- **Intuition**: Think of a ball rolling downhill; it picks up speed (and hence momentum) as it goes.

# Nesterov Accelerated Gradient (NAG)

## The ”look-ahead” Strategy

- **Improvement over Momentum**: Takes a ”look-ahead” gradient step.
- **Update Rule**:

$$v_{t+1} = \gamma v_t + \eta \nabla_\theta L(\theta_t - \gamma v_t)$$
$$\theta_{t+1} = \theta_t - v_{t+1}$$

- **Intuition**: Imagine you are rolling down while looking ahead to adjust your path.
- **Benefit**: Faster and potentially more accurate convergence.

# Adaptive Gradient (AdaGrad)

## Introducing Adaptivity

- **Adapting Learning Rates**: Adjusts the learning rates for each parameter during training.
- **Update Rule**:

$$G_{t+1,ii} = G_{t,ii} + (\nabla_\theta L(\theta_t))_i^2$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{G_{t+1} + \epsilon}} \cdot \nabla_\theta L(\theta_t)$$

- Add $\epsilon$ (small) to prevent division by zero, typically $1 \times 10^{-8}$.
- **Benefit**: Good for sparse data and features that appear infrequently.

# Adaptive Moment Estimation (Adam)

## Best of Both Worlds

- **Combination of Momentum and AdaGrad**: Keeps track of past gradients and their squares.
- **Update Rule**:

$$m_{t+1} = \beta_1 m_t + (1 - \beta_1)\nabla_\theta L(\theta_t)$$

$$v_{t+1} = \beta_2 v_t + (1 - \beta_2)(\nabla_\theta L(\theta_t))^2$$

$$\hat{m}_{t+1} = \frac{m_{t+1}}{1 - \beta_1^{t+1}}$$

$$\hat{v}_{t+1} = \frac{v_{t+1}}{1 - \beta_2^{t+1}}$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_{t+1}} + \epsilon}\hat{m}_{t+1}$$

- **Common values:** $\beta_1 = 0.9$, $\beta_2 = 0.999$, $\epsilon = 1 \times 10^{-8}$.
- **Benefit**: Incorporates adaptivity and momentum. Often recommended as default optimizer in deep learning.

# Questions and Discussion

1. **Which Optimizer Outperformed Others?**
   - Which optimizer do you usually choose?
   - Do you usually experiment with different optimizers?
   - Share your experience with the others
2. **Areas for Improvement?**
   - How can we improve the optimization results?
3. **Further Exploration**
   - Why do we rarely use second-order methods in deep learning?
   - Does *Learning Rate Scheduling* make sense for adaptive methods?
   - What about *Gradient-Clipping* for Momentum?

# Final Thoughts and Conclusion

## Summary

- Successfully implemented and compared (1) SGD, (2) Momentum, (3) Nesterov, (4) AdaGrad, (5) Adam on MNIST.
- Each has merits and drawbacks, which we discussed.

## Limitations

- This is not an exhaustive list; many other algorithms exist, such as *Adadelta*, *RMSProp*, and *Nadam*.
- Importance of hyperparameter tuning for achieving the best results.

## Key Takeaways

- Optimization algorithm nuances and choice are key to model training.
- Tuning hyperparameters are critical steps, not just ‘set-and-forget’ decisions.
- Better understanding boosts confidence in optimizer choice.

# Thank You!

## Thank You For Your Attention!


## Any Questions?