Introduction to Machine Learning

Module 1D: Regularization

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Complex Models Need Regularization

In ML, we use highly complex models with many adjustable parameters.

- Learning the noise in data?

Source:
https://miro.medium.com/max/1600/1*hx--qD6l1p2ruJSbDSJW6A.jpeg

Model Complexity Matters!

- Too simple -> “underfits”

Source:
https://pics.me.me/me-wondering-why-my-ai-is-classifying-my-cat-as-72552652.png

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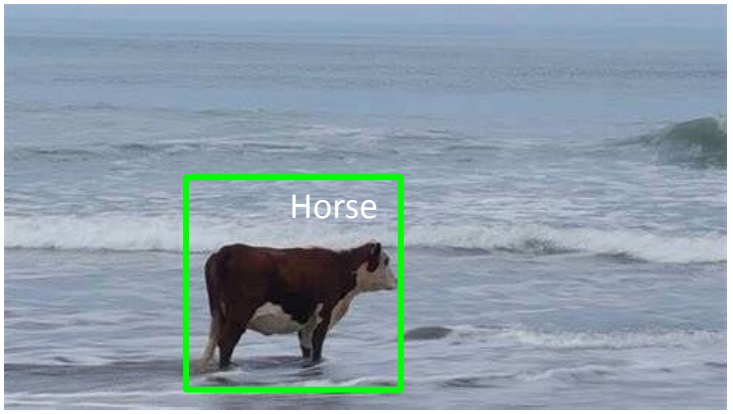
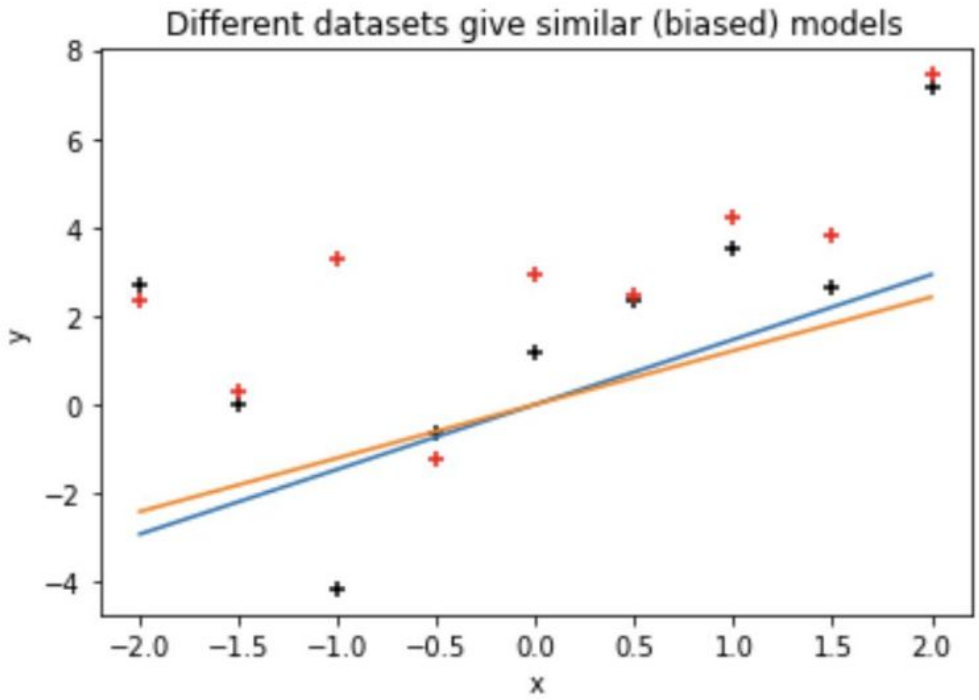


Source:
https://th.bing.com/th/id/OIP.1txVEjak0Qzx1dHGqqAypQHaEU?w=300&h=180&c=7&r=0&o=5&pid=1.7

Model Complexity Matters!

Bias vs Variance Tradeoff

- Bias: The simple models often give systematically too small weights.



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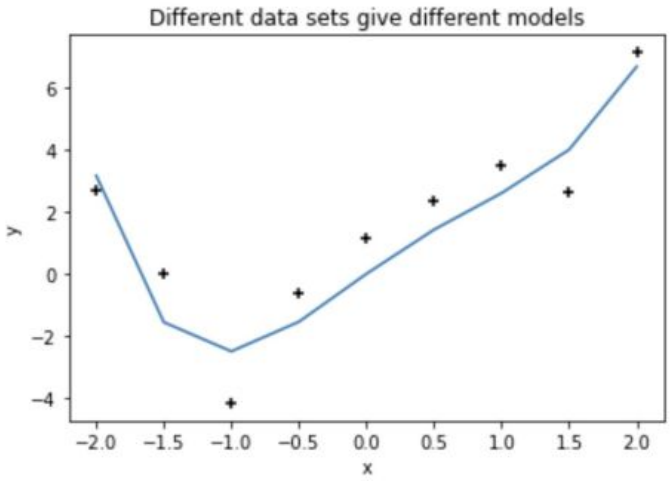
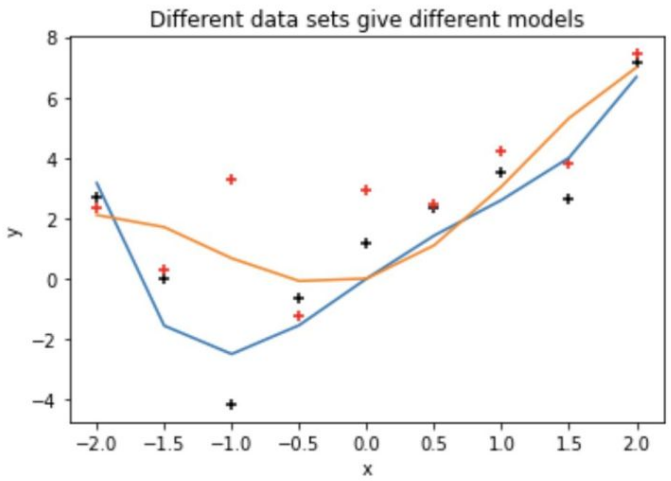
Bias vs Variance Tradeoff

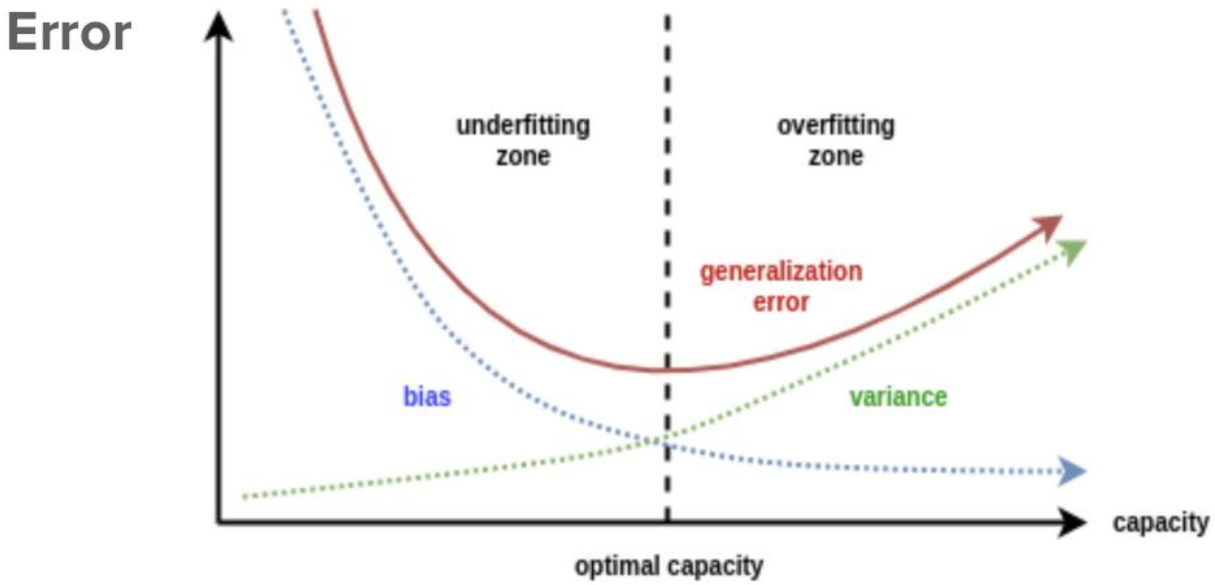
- Bias: The simple models often give systematically too small weights.
- Variance: The complex model capture the variance too much that leads to poor generalization





Model Complexity Matters!

How to pick right model complexity?



Source:https://images.deepai.org/

Model Complexity Matters!

The magic!

Deep learning on images (Zhang, Bengio, Hardt, Recht, and Vinyalsn 2017)

- gives 0 training error -- and small test error
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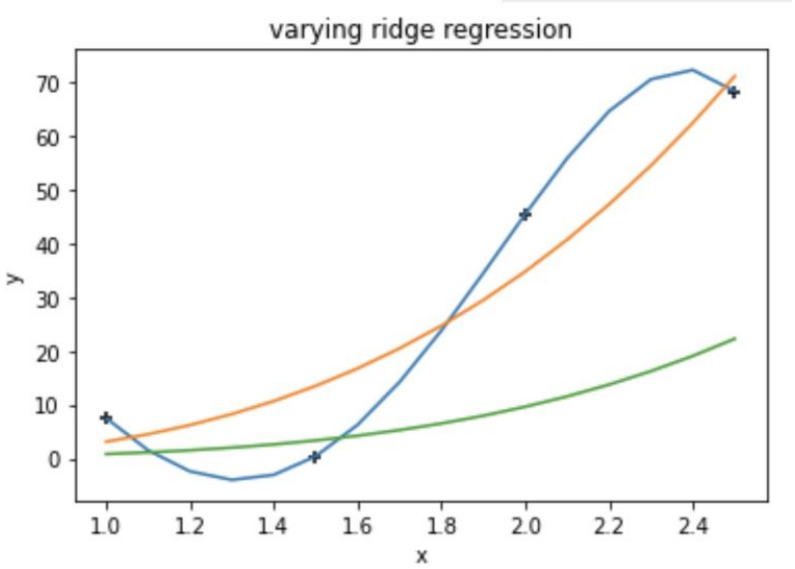
R2 detour.

Characteristics of Regularized Models

The more regularized models give us:

- Smaller weights (less fitting to noise)
- Smoother models
- Models with lower capacity



Let’s get start to our first tutorial!

Common Regularization Techniques

L1 and L2 penalties:

- Train to minimize normal loss + c * L1(weights)
  - L1: Lasso regression
  - Drives some weights to 0

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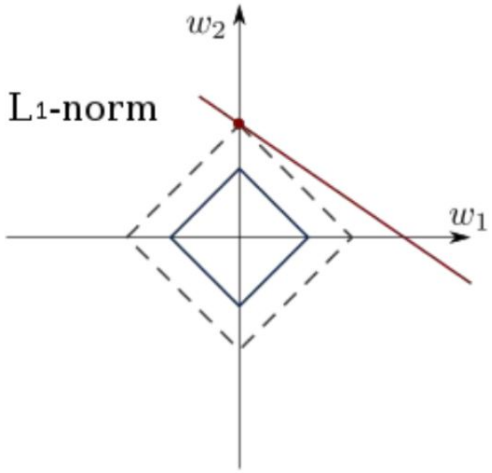

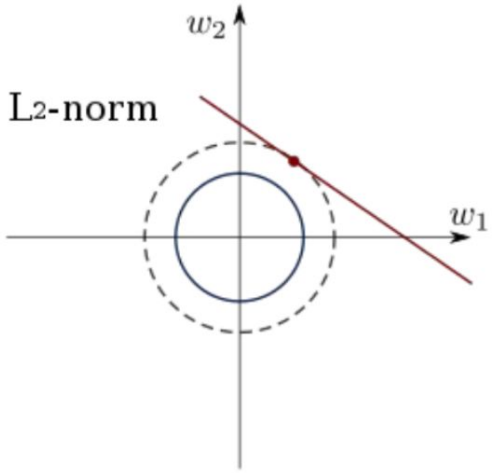

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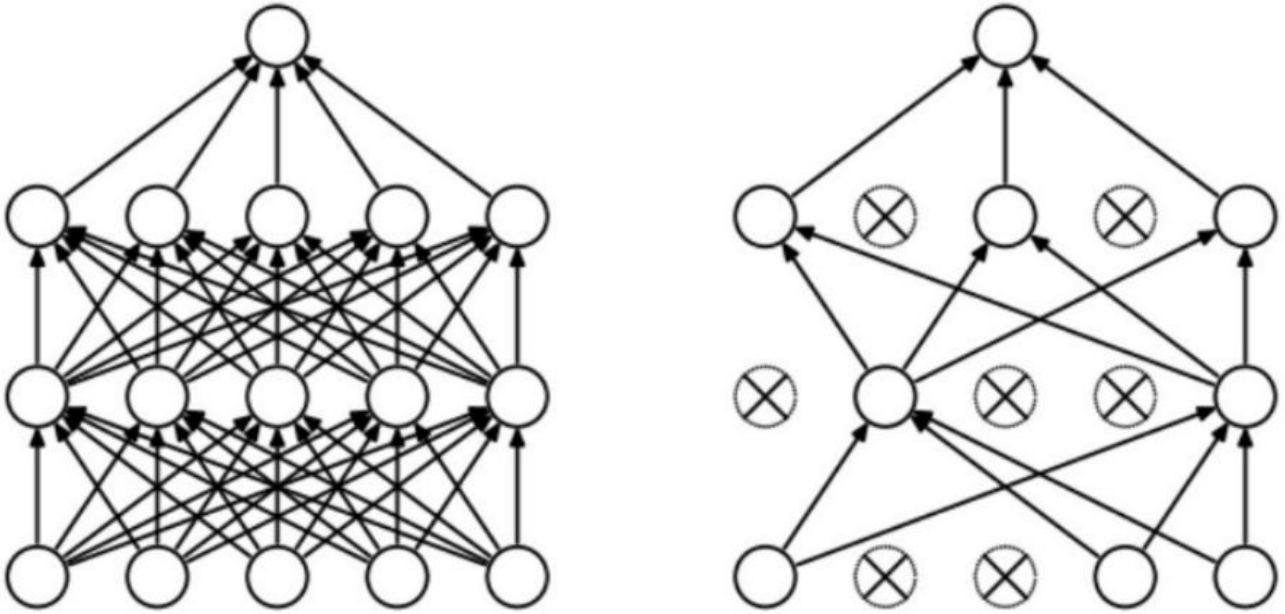
L-infinity penalty:

- Train to minimize normal loss - but don’t let the weights get too big

Common Regularization Techniques

Drop-out



(a) Standard Neural Net

(b) After applying dropout.

Common Regularization Techniques

Data Augmentation

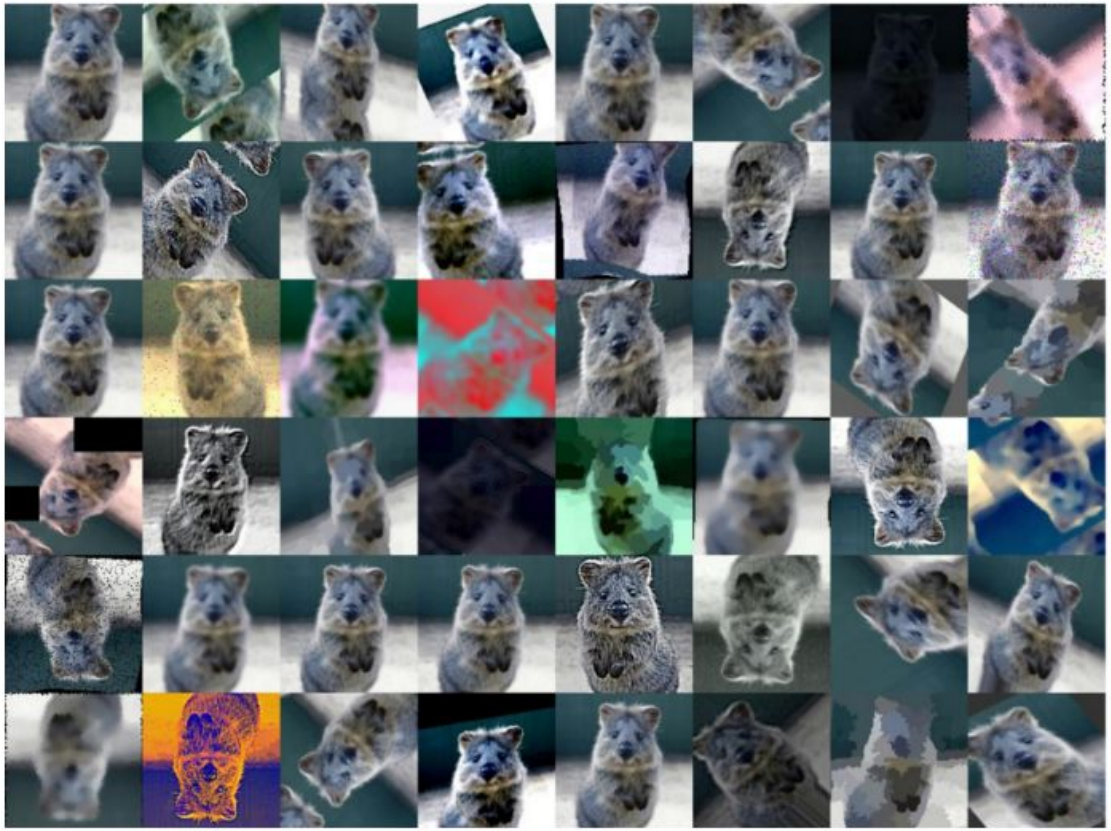
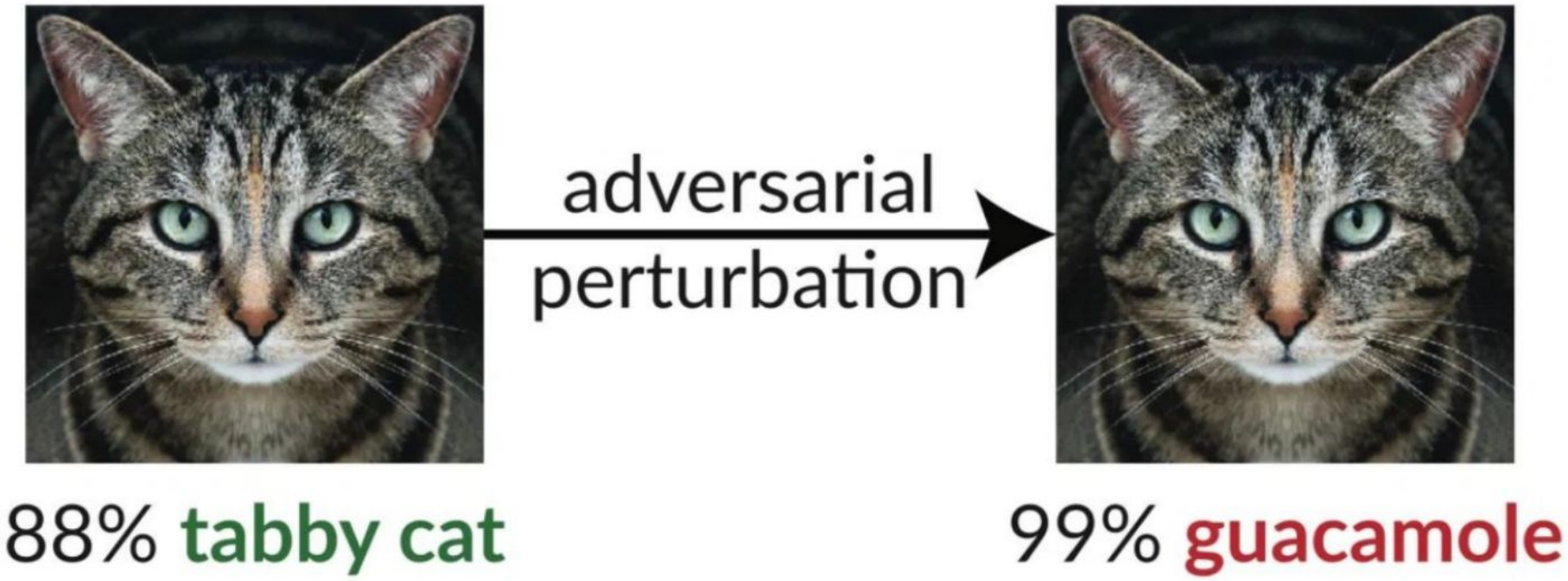


Image Augmentation Sample. Image by https://github.com/aleju/imgaug

Bonus: Adversarial Attacks



Common Regularization Techniques

Stochastic Gradient Descent (SGD)

- Initialize with small random weights
- Weights get bigger as one iterates
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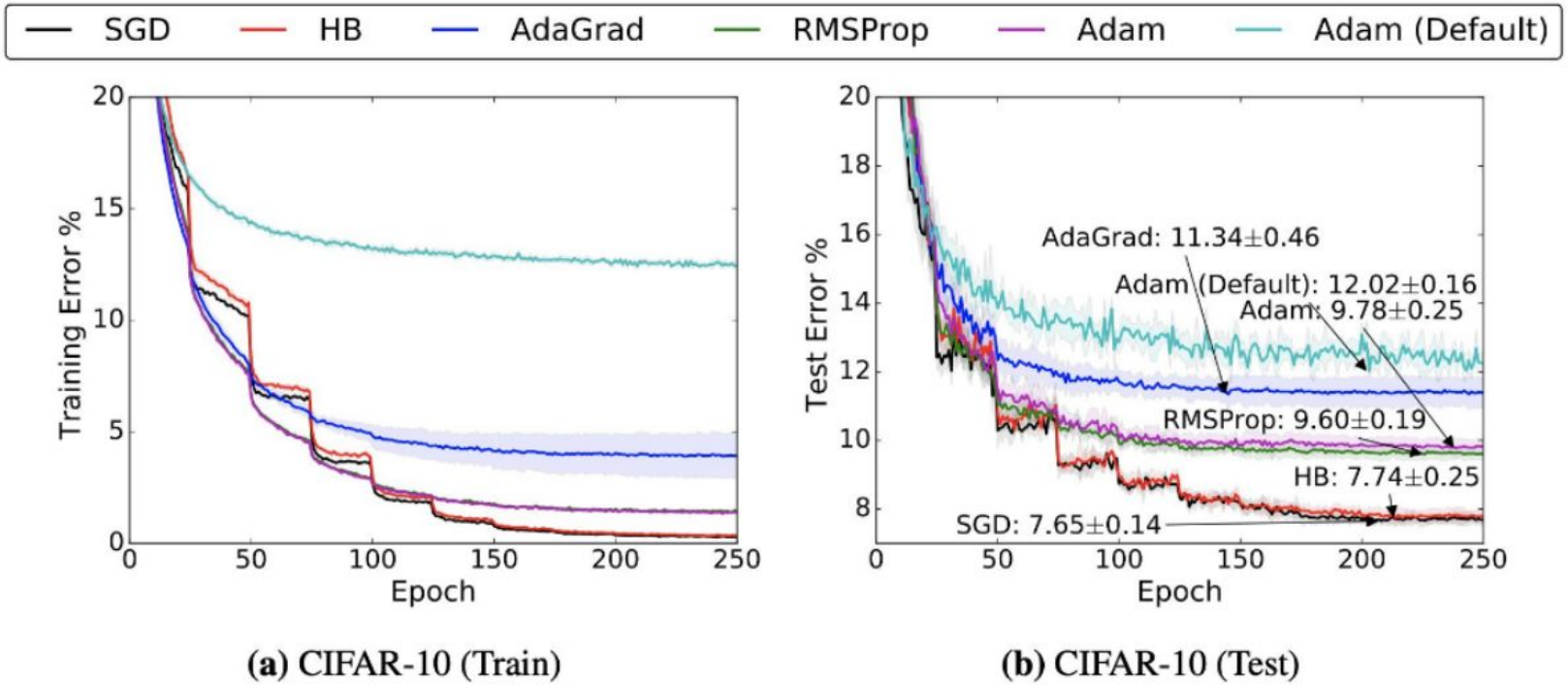

(a) CIFAR-10 (Train)

(b) CIFAR-10 (Test)

Common Regularization Techniques

Learning rates and regularization

- Small learning rates are more likely to find a deep minimum -> might be good or bad

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- Small learning rates are more likely to find a deep minimum -> might be good or bad
- Large learning rates misses deep minimas, finds broader and flatter minimas that may be more robust.

Common Regularization Techniques

Conclusion on regularization techniques: Use all!

Common Regularization Techniques

Hyperparameter tuning is a search:

- **Grid Search:** Try all possible combinations of hyperparameters
- **Random Search:** Randomly try different combinations of hyperparameters
- **Coordinate-wise Gradient Descent:** Start at one set of hyperparameters and try changing one at a time, accept any changes that reduce your validation error
- **Bayesian Optimization / Auto ML:** Start from a set of hyperparameters that have worked well on a similar problem, and then do some sort of local exploration (e.g., gradient descent) from there.

Let's start to our final tutorial today!!