**Papers for optimization/learning algorithms:**

ADMM and accelerated ADMM as continuous dynamical systems

<http://proceedings.mlr.press/v80/franca18a.html>

Characterizing implicit bias in terms of optimization geometry

<http://proceedings.mlr.press/v80/gunasekar18a.html>

The implicit bias of gradient descent on separable data

<https://arxiv.org/abs/1710.10345>

Stochastic gradient/mirror descent: Minimax optimality and implicit regularization

<https://arxiv.org/abs/1806.00952>

A PID controller approach for stochastic optimization of deep networks

<https://www4.comp.polyu.edu.hk/~cslzhang/paper/CVPR18_PID.pdf>

On the expected convergence of randomly permuted ADMM

<https://arxiv.org/abs/1503.06387>

Gradient descent finds global minima of deep neural networks

<https://arxiv.org/abs/1811.03804>

Gradient descent learns one-hidden-layer CNN: Don’t be afraid of spurious local minima

<https://arxiv.org/abs/1712.00779>

A convergence theory for deep learning via over-parameterization

<https://arxiv.org/abs/1811.03962>

**Papers for reinforcement learning and control:**

Global convergence of policy gradient methods for linearized control problems:

<https://arxiv.org/abs/1801.05039>

Robust adversarial reinforcement learning

<https://arxiv.org/abs/1703.02702>

Reinforcement learning applied to linear quadratic regulation

<https://papers.nips.cc/paper/712-reinforcement-learning-applied-to-linear-quadratic-regulation.pdf>

On the sample complexity of the linear quadratic regulator

<https://arxiv.org/abs/1710.01688>

Model-free linear discrete-time system H-infinity control using input-output data

<https://ieeexplore.ieee.org/abstract/document/8506843>

Trust region policy optimization

<https://arxiv.org/abs/1502.05477>

PLATO: policy learning using adaptive trajectory optimization

<https://arxiv.org/abs/1603.00622>

Nonsmooth H-infinity synthesis

<https://ieeexplore.ieee.org/abstract/document/1576856/>

Deep reinforcement learning that matters

<https://arxiv.org/abs/1709.06560>

Stochastic variance reduction methods for policy evaluation

<https://arxiv.org/abs/1702.07944>

Learning-based model predictive control for safe exploration

<https://arxiv.org/abs/1803.08287>

The Lyapunov neural network: adaptive stability certification for safe learning of dynamic systems

<https://arxiv.org/abs/1808.00924>

Learning model predictive control for iterative tasks: A data-driven control framework

<https://ieeexplore.ieee.org/document/8039204>

Safe model-based reinforcement learning with stability guarantees

<https://arxiv.org/abs/1705.08551>

Safe end-to-end imitation learning for model predictive control:

<https://arxiv.org/abs/1803.10231>

Robust synthesis for linear parameter varying systems using integral quadratic constraints

<https://www.sciencedirect.com/science/article/pii/S0005109816000546>

Variance reduction for policy gradient with action-dependent factorized baselines

<https://arxiv.org/abs/1803.07246>

**Robotic learning:**

End-to-end training of deep visuomotor policies:

<https://arxiv.org/abs/1504.00702>

**Other options:**

One option is that you can choose a control problem you are interested in and then try to apply the RL methods taught in the class to this specific problem. Then in the presentation, you will be asked to talk about the background of the problem and highlight which methods you want to try for this problem.

Another option is just to try to extend the results covered in the class. For example, in the class we talked about the policy gradient method and other RL methods for linear quadratic control of LTI systems. One natural question is whether we can extend the results for LPV systems or other types of systems.

 Actually you are allowed to choose any paper related to the fields of control, learning, and optimization.