SEA	RCH	Q	
RES	OURCES	A	
CON	NCEPTS		
Y	16. Environment Classification	•	
S	17. Frenet Reminder		

✓ 18. The Need for Time

19. s, d, and t

20. Trajectory Matching

21. Structured Trajectory Generati...

22. Trajectories with Boundary Co...

23. Jerk Minimizing Trajectories

24. Derivation Overview

25. Derivation Details 2

26. Polynomial Trajectory Generat...

27. Implement Quintic Polynomial...

28. Implement Quintic Polynomial...

✓ 29. What should be checked?

30. Implementing Feasibility

31. Putting it All Together

32. Polynomial Trajectory Reading...

☑ 33. Polynomial Trajectory Generat...

34. Conclusion

35. Bonus Round: Path Planning ...



Mentor Help

Ask a mentor on our Q&A platform



Peer Chat Chat with peers and alumni

Additional Resources on Path Planning

Nice work reaching the end of the path planning content! While you still have the project left to do here, we're also providing some additional resources and recent research on the topic that you can come back to if you have time later on.

Reading research papers is a great way to get exposure to the latest and greatest in the field, as well as expand your learning. However, just like the project ahead, it's often best to *learn by doing* - if you find a paper that really excites you, try to implement it (or even something better) yourself!

Optional Reading

All of these are completely optional reading - you could spend hours reading through the entirety of these! We suggest moving onto the project first so you have what you've learned fresh on your mind, before coming back to check these out.

We've categorized these papers to hopefully help you narrow down which ones might be of interest, as well including their *Abstract* section, which summarizes the paper.

Indoors

Intention-Net: Integrating Planning and Deep Learning for Goal-Directed Autonomous Navigation by S. W. Gao, et. al.

Abstract: How can a delivery robot navigate reliably to a destination in a new office building, with minimal prior information? To tackle this challenge, this paper introduces a two-level hierarchical approach, which integrates model-free deep learning and model-based path planning. At the low level, a neural-network motion controller, called the intention-net, is trained end-to-end to provide robust local navigation. The intention-net maps images from a single monocular camera and "intentions" directly to robot controls. At the high level, a path planner uses a crude map, e.g., a 2-D floor plan, to compute a path from the robot's current location to the goal. The planned path provides intentions to the intention-net. Preliminary experiments suggest that the learned motion controller is robust against perceptual uncertainty and by integrating with a path planner, it generalizes effectively to new environments and goals.

City Navigation

Learning to Navigate in Cities Without a Map by P. Mirowski, et. al.

Abstract: Navigating through unstructured environments is a basic capability of intelligent creatures, and thus is of fundamental interest in the study and development of artificial intelligence. Long-range navigation is a complex cognitive task that relies on developing an internal representation of space, grounded by recognizable landmarks and robust visual processing, that can simultaneously support continuous self-localization ("I am here") and a representation of the goal ("I am going there"). Building upon recent research that applies deep reinforcement learning to maze navigation problems, we present an end-to-end deep reinforcement learning approach that can be applied on a city scale. [...] We present an interactive navigation environment that uses Google StreetView for its photographic content and worldwide coverage, and demonstrate that our learning method allows agents to learn to navigate multiple cities and to traverse to target destinations that may be kilometers away. [...]

Intersections

A Look at Motion Planning for Autonomous Vehicles at an Intersection by S. Krishnan, et. al.