The AI Driving Olympics

Contents

Part A - Introduction ................................................................. 2

Part B - The Challenges ............................................................. 10

Part C - Getting Started .............................................................. 19

Part D - Template Solutions ....................................................... 33

Part E - Baseline Algorithms ....................................................... 45

Part F - Reference manual ......................................................... 72

Part G - References ................................................................. 78
PART A
Introduction

Contents

Unit A-1 - The AI Driving Olympics ................................................................. 3
Unit A-2 - The Duckietown Platform ............................................................... 6
The AI Driving Olympics (AI-DO) is a set of competitions with the objective of evaluating the state of the art in machine learning and artificial intelligence for mobile robotics. For a detailed description of the scientific objectives and outcomes please see our recent paper about the AI-DO 1 at NeurIPS.

Contents
Section 1.1 - History........................................................................................................................................................................3
Section 1.2 - Leagues ......................................................................................................................................................................4
Section 1.3 - What’s new in the Urban League in AI-DO 5.................................4
Section 1.4 - How to use this documentation .......................................................5
How to get help........................................................................................................................................................................5

1.1. History
• AI-DO 1 was in conjunction with NeurIPS 2018.
• AI-DO 2 was in conjunction with ICRA 2019.
• AI-DO 3 was in conjunction with NeurIPS 2019.
• AI-DO 4 was supposed to be in conjunction with ICRA 2020, but was canceled due to COVID-19.
• AI-DO 5 is in conjunction with NeurIPS 2020.
1.2. Leagues

There are currently two leagues in the AI Driving Olympics. The **Urban League** is based on the Duckietown platform, and includes a series of tasks of increasing complexity. For each task, we provide tools for competitors to use in the form of simulators, logs, code templates, baseline implementations and low-cost access to robotic hardware. We evaluate submissions in simulation online, on standardized hardware environments, and finally at the competition event. Participants will not need to be physically present at any stage of the competition — they will just need to send their source code. There will be qualifying rounds in simulation, similar to recent DARPA Robotics Challenges, and, for evaluation, we make available the use of “Duckietown Autolabs” which are facilities that allow remote experimentation in a reproducible setting.

See the leaderboards and many other things at the challenges site.

The **Advanced Perception League** is organized by Motional (ex nuTonomy, Aptiv Mobility). This book describes the urban league. All information about the Advanced Perception League is at nuScenes.org.

1.3. What’s new in the Urban League in AI-DO 5

There have been many cool new improvements for the 5 edition of the AI-DO Urban League:

- The robots in the simulators and the new DB19 Duckiebots are equipped with **encoders**.
- In the new **LFP** challenge there are now duckie-pedestrians to avoid.
- In the **LFV_multi** challenge you control **all** of the robots in a multi-vehicle setting, instead of just one.
- The agents can now control the **LEDs** in the simulator.

Furthermore, there were many improvements to the back-end and baseline workflows to help you get started.
1.4. **How to use this documentation**

If you would like to compete in the AI-DO Urban League, you will probably want to do something like:

- Read the brief introduction to the competition (~5 mins).
- Find the challenge that you would like to try (~5 mins).
- Get started and make a submission (~5-20 mins depending on your setup).

At this point you are all setup, can make a submission, and you should want to make your submission better. To do this the following tools might prove useful:

- The AIDO API so that your workflow is efficient using our tools.
- The reference algorithms where we have implemented some different approaches to solve the challenges.

**How to get help**

If you are stuck try one of the following things:

- Look through the contents of this documentation using the links on the left. Note that the “Parts” have many “Chapters” that you can see when you click on the Part title,
- Join our slack community,
- If you are sure you actually found a bug, file a github issue in the appropriate repo.

**How to cite**

If you use the AI-DO platform in your work and want to cite it please use:

```
@article{zilly2019ai,
  title={The AI Driving Olympics at NeurIPS 2018},
  author={Julian Zilly and Jacopo Tani and Breandan Considine and Bhairav Mehta and Andrea F. Daniele and Manfred Diaz and Gianmarco Bernasconi and Claudio Ruch and Jan Hakenberg and Florian Golemo and A. Kirsten Bowser and Matthew R. Walter and Ruslan Hristov and Sunil Mallya and Emilio Frazzoli and Andrea Censi and Liam Paull},
  year={2019}
}
```
UNIT A-2
The Duckietown Platform

This section focuses on the physical platform used for the embodied individual robotic challenges.

For examples of Duckiebot driving see a set of demo videos of Duckiebots driving in Duckietown.

The actual embodied challenges will be described in more detail in LF, LFV_multi, LFP. Note that the sequence challenges was chosen to gradually increase the difficulty of challenges by extending previous challenge solutions to more general situations.

Contents
Section 2.1 - The Duckietown Platform.................................................................6
Section 2.2 - Duckiebots and Duckietowns............................................................6

2.1. The Duckietown Platform
There are three main parts in our system with which the participants will interact:

1. **Simulation and training** environment, which allows to test in simulation before trying on the real robots.

2. **Duckietown Autolabs** in which to try the code in controlled and reproducible conditions.

3. **Physical Duckietown platform**: miniature vision-based vehicles and cities in which the vehicles drive. The robot hardware and environment are rigorously specified, which makes the development extremely repeatable (For an example of this see “Duckietown specifications”. If you have a Duckiebot then you will want to refer to the Duckiebot manual. If you would like to acquire a Duckiebot please go to get.duckietown.org.

2.2. Duckiebots and Duckietowns
We briefly describe the physical Duckietown platform, which comprises autonomous vehicles (*Duckiebots*) and a customizable model urban environment (*Duckietown*).

1) The Duckiebot
Duckiebots are designed with the objectives of affordability, modularity and ease of construction. They are equipped with: a front viewing camera with 0 deg fish-eye lens capable of streaming 0 0 resolution images reliably at 0 fps, and wheel encoders on the motors.

*Actuation* is provided through two DC motors that independently drive the front wheels (differential drive configuration), while the rear end of the Duckiebot is equipped with a passive omnidirectional wheel.
All the computation is done onboard on a Raspberry Pi 3B+ computer, equipped with a quad Core 1.4 GHz, 64 bit CPU and 1 GB of RAM. We will support other configurations for the purposes of deploying neural networks onto the robots.

Power is provided by a 0000 mAh battery which provides several hours of operation.

2) The Duckietown

Duckietowns are modular, structured environments built on two layers: the road and the signal layers (Figure 2.2). Detailed specifications can be found here.

There are six well defined road segments: straight, left and right 0 deg turns, 3-way intersection, 4-way intersection, and empty tile. Each is built on individual tiles, and their interlocking enables customizability of city sizes and topographies. The appearance specifications detail the color and size of the lines as well as the geometry of the roads.

The signal layer comprises of street signs and traffic lights. Street signs enable global localization (knowing where they are within a predefined map) of Duckiebots in the city and interpretation of intersection topologies. They are defined as the union of an AprilTag [1] in addition to the typical road sign symbol. Their size, height and relative positioning with respect to the road are specified. Many signs are supported, including intersection type (3- or 4-way), stop signs, road names, and pedestrian crossings.

The Duckietown environment is rigorously defined at road and signal level. When the appearance specifications are met, Duckiebots are guaranteed to navigate cities of any topology.

Figure 2.2

3) Simulation

We provide a cloud simulation environment for training.

In a way similar to the last DARPA Robotics Challenge, we use the simulation as a first screening of the participants. It will be necessary for the code to run in simulation to gain access to the Autolabs. In particular we emphasize that Duckiebots should not crash in simulation since a similar behavior may be disruptive to the physical Ducki-
etown.

Simulation environments for each of the individual challenges will be provided as Docker containers with clearly specified APIs. The baseline solutions for each challenge will be provided as separate containers. When both containers (the simulation and corresponding solution) are loaded and configured correctly, the simulation will effectively replace the real robot(s). A proposed solution can be uploaded to our cloud servers, at which point it will be automatically run against our pristine version of the simulation environment (on a cluster) and a score will be assigned and returned to the uploader.

Examples of the simulators provided are shown in Figure 2.4. The left panel shows a lightweight simulator with low-level timing control built on OpenGL. This simulator is also integrated with the OpenAI Gym environment for reinforcement learning agent training. An API for designing reward functions or tweaking domain randomization will be provided.

![Lightweight simulation environment for training and development](image)

Figure 2.4

4) Duckietown Autolabs

![The robotarium at ETH Zürich](image)

Figure 2.6

The idea of a robotarium (contraction of *robot* and *aquarium*) was conceived at Georgia Tech [2]. The use of a robotarium has two main advantages:

1. **Convenience:** It allows convenient access to a complete robot setup.
2. **Reproducibility:** It allows for multiple people to run the experiments in repeatable controlled conditions.
The Duckietown robotariums will be built in the following institutions:

1. ETH Zürich;
2. University of Montréal;
3. TTI Chicago.

For the competition we will several options for computational power.

1. The “purist” computational substrate option: the only computation available is the Raspberry PI 3B+ processor on board.
2. The images are streamed to a basestation with a powerful GPU. This will increase computational power but also increase the latency in the control loop.
# PART B

## The Challenges

This section precisely defines the general rules and performance metrics and explains each of the 3 challenges.

## Contents

<table>
<thead>
<tr>
<th>Unit</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>B-1</td>
<td>General rules</td>
<td>11</td>
</tr>
<tr>
<td>B-2</td>
<td>Performance metrics</td>
<td>13</td>
</tr>
<tr>
<td>B-3</td>
<td>Challenge LF</td>
<td>15</td>
</tr>
<tr>
<td>B-4</td>
<td>Challenge LFP</td>
<td>17</td>
</tr>
<tr>
<td>B-5</td>
<td>Challenge LFV_multi</td>
<td>18</td>
</tr>
</tbody>
</table>
UNIT B-1
General rules

Contents
Section 1.1 - Protocol .................................................................................................................................11
Section 1.2 - Eligibility .....................................................................................................................................12
Section 1.3 - Intellectual property ..................................................................................................................12

1.1. Protocol

1) Deployment technique
We use Docker containers to package, deploy, and run the applications on the physical Duckietown platform as well as on the cloud for simulation. Base Docker container images are provided and distributed via Docker HUB.
A challenges server is used to collect and queue all submitted agents. The simulation evaluations execute each queued agents as they become available. Submissions that pass the simulation environment will be queued for execution in the Autolab.
For validation of submitted code and evaluation the competition finals a surprise environment will be employed. This is to discourage overfitting to any particular Duckietown configuration.

2) Submission of entries
Participants can submit their code in the form of a docker container to a task. Scripts are provided for creating the container image in a conforming way.
The system will schedule to run the code on the cloud on the challenges selected by the user, and, if simulations pass, on the Autolabs.
Participants can submit entries as many times as they would like. Access control policies are to be implemented, should certain participants monopolize the computational and physical resources available.
Participants are required to open source their solutions source code. If auxiliary training data are used to train the models, that data must be made available.
Submitted code will be evaluated in simulation and if sufficient on physical Autolabs. Scores and logs generated with submitted code will be made available.
Simulation code is available as open source for everybody to use on computers that they control. The simulators interact with the simulator through a standardized interfaces that mimics the interface with the real robot.

3) Autolab test and validation
When an experiment is run in a training/testing Autolab, the participants receive, in addition to the score, detailed feedback, including logs, telemetry, videos, etc. The sensory data generated by the robots is continuously recorded and becomes available im-
mediately to the entire community.

When an experiment is run in a validation Autolab, the only output to the user is the test score and minimal statistics (number of collisions, number of rule violations, etc.)

4) Leaderboards

After each run in an Autolab, the participants can see the metrics statistics on the competition scoring website.

1.2. Eligibility

Employees and affiliates of Motional/SwissRe are ineligible from participation in the competition. Employees and affiliates of Motional/SwissRe may submit baseline solutions that will be reported in a special leaderboard.

Students of ETH Zürich, Montreal, and TTIC, are eligible to participate in the competition as part of coursework, if they do not work in the organization of the competition.

1.3. Intellectual property

Participants of AI-DO are required to provide the source code / data / learning models of their submission to the organizers before the finals (so that we can check for their regularity.)

Winners of AI-DO are required to make their submission open source so that it can be reused later in the next challenges.
Measuring performance in robotics is less clear cut and more multidimensional than traditionally encountered in machine learning settings. Nonetheless, to achieve reliable performance estimates we assess submitted code on several episodes with different initial settings and compute statistics on the outcomes. We denote $J$ to be an objective or cost function to optimize, which we evaluate for every experiment. In the following formalization, objectives are assumed to be minimized.

In the following we summarize the objectives used to quantify how well an embodied task is completed. We will produce scores in three different categories.

2.1. Performance criteria (P)

As a performance indicator for both the “lane following task” and the “lane following task with other dynamic vehicles”, we choose the integrated speed $v(t)$ along the road (not perpendicular to it) over time of the Duckiebot. This measures the moved distance along the road per episode, where we fix the time length of an episode. This encourages both faster driving as well as algorithms with lower latency. An episode is used to mean running the code from a particular initial configuration.

$$J_{P-LF(V)}(t) = \int_0^t -v(t)\,dt$$

The integral of speed is defined over the traveled distance of an episode up to time $t = T_{eps}$, where $T_{eps}$ is the length of an episode.

The way we measure this is in units of “tiles traveled”:

$$J_{P-LF(V)}(t) = \# \text{ of tiles traveled}$$

2.2. Traffic law objective (T)

The following shows rule objectives the Duckiebots are supposed to abide by within Duckietown. These penalties hold for the embodied tasks (LF, LFV).

1) Major infractions

This objective means to penalize “illegal” driving behavior. As a cover for many undesired behaviors, we count the median time spent outside of the drivable zones. This also
covers the example of driving in the wrong lane.
Metric: The median of the time spent outside of the drivable zones.

\[ J_{T-LF/LFV} = \text{median}(\{t_{outside}\}), \]
where \( \{t_{outside}\} \) is the list of accumulated time outside of drivable zones per episode.

2.3. Comfort objective (C)
In the single robot setting, we encourage “comfortable” driving solutions. We therefore penalize large angular deviations from the forward lane direction to achieve smoother driving. This is quantified through changes in Duckiebot angular orientation \( \theta_{bot}(t) \) with respect to the lane driving direction.

_Lateral deviation:_
For better driving behavior we measure the median per episode lateral deviation from the right lane center line.

\[ J_{C-LF/LFV} = \text{median}(\{d_{outside}\}), \]
where \( \{d_{outside}\} \) is the sequence of lateral distances from the center line.
UNIT B-3
Challenge LF

The first challenge of the AI Driving Olympics is “lane following” (LF).
In this challenge, we ask participants to submit code allowing the Duckiebot to drive on the right-hand side of the street within Duckietown without a specific goal point. Duckiebots will drive through the Duckietown and will be judged on how fast they drive, how well they follow the rules and how smooth or “comfortable” their driving is. Please refer to the following video of a lane following demo for a short demonstration. A description of the specific rules is provided.

![Figure 3.2](image)

Figure 3.2

Figure 3.1. A Duckiebot doing lane following

The challenge is designed in a way that should allow for a completely reactive algorithm design. This meant to say that to accomplish the challenge, it should not be strictly necessary to keep past observations in memory. In particular intersections will not be part of this challenge. Intersections will be recognized and maneuvered using provided code from the organizers.

3.1. LF in Simulation

The current versions of the lane following simulation challenge are aido5-LF-sim-testing and aido5-LF-sim-validation. These two challenges are identical except for the output that you are allowed to see. In the case of testing you will be able to see performance of your agent (Figure 3.4) and you will be able to download the logs and artifacts.
Figure 3.4

Figure 3.3. Visual output for submission
UNIT B-4
Challenge LFP

This challenge is an extension of Challenge LF to include duckie pedestrians.

Figure 4.1. Avoid the duckie-pedestrians

Again we ask participants to submit code allowing the Duckiebot to drive on the right-hand side of the street within Duckietown, but now it must also avoid duckie pedestrians.

4.1. LFP in Simulation

The current versions of the lane following with pedestrians in simulation are aido5-LFP-sim-testing and aido5-LFP-sim-validation. These two challenges are identical except for the output that you are allowed to see. In the case of testing you will be able to see performance of your agent (Figure 4.4) and you will be able to download the logs and artifacts.

Figure 4.4

Figure 4.3. Visual output for submission
This challenge is an extension of Challenge LF to include additional rules of the road and other moving vehicles. In this challenge your agent embodies *all of the vehicles on the road.

Figure 5.2

Figure 5.1. A Duckiebot doing lane following with other vehicles

Again we ask participants to submit code allowing the Duckiebot to drive on the right-hand side of the street within Duckietown.

5.1. LFV_multi in Simulation

The current versions of the lane following with vehicles in simulation are aido5-LFV_multi-sim-testing and aido5-LF-sim-validation. These two challenges are identical except for the output that you are allowed to see. In the case of testing you will be able to see performance of your agent (Figure 5.4) and you will be able to download the logs and artifacts.

Figure 5.4

Figure 5.3. Visual output for submission
PART C
Getting Started

This part describes the necessary steps to get started competing in the AI-DO. It should take about 5-20 minutes depending on your specific setup. In short, the steps are the following:

- Get the needed accounts;
- Make sure you meet the software requirements;
- Make a test submission.

Figure 0.5. Getting Started

At this point you have a fully functioning setup and you can start to build a solution to the specific challenge that you interested in. In this section, we provide two additional quickstart guides as entrypoints:

Contents

Figure 0.5 - Getting Started

Unit C-1 - Accounts needed .................................................................20
Unit C-2 - Software requirements .......................................................21
Unit C-3 - Make your first submission ..................................................24
Unit C-4 - Next steps towards winning the AI-DO .................................26
Unit C-5 - Run an agent on your Duckiebot ........................................28
Unit C-6 - Object Detection Dataset .....................................................30
This section describes the accounts that you need before competing.

1.1. Docker Hub account
A Docker Hub account is necessary to submit container images.
Create an account here. Take note of your USERNAME.

1.2. Duckietown account
A Duckietown account is necessary to interact with the challenges server.
Create an account here.

1.3. Stack Overflow account
We have a Stack Overflow for Duckietown. We will send you an invite when you register. Otherwise, please ask us on Slack.
This section describes the required software to participate in the competition.

### 2.1. Supported Operating Systems

1) **Ubuntu 20.04**

Ubuntu 20.04 is the best supported environment. Earlier version might work. Note that we require an environment with Python 3.8 or higher.

2) **Other GNU/Linux versions**

Any other GNU/Linux OS with Python of at least version 3.8 should work. However, we only support officially Ubuntu.

3) **Mac OS X**

OS X is well supported; however we don’t have full instructions for certain steps. (There is so much divergence in how OS X environments are configured.)

We suggest to use `pyenv` to install Python 3.8.

4) **Windows**

Windows is currently not supported. We are working on it! Please let us know if can help.

### 2.2. Docker

Install Docker from these instructions.

If you want to use a GPU for evaluating your submission, edit your `/etc/docker/daemon.json` to include the following options.

```json
{
    "default-runtime": "nvidia",

    "runtimes": {
        "nvidia": {
            "path": "nvidia-container-runtime",
            "runtimeArgs": []
        }
    }
}

"node-generic-resources": [ "NVIDIA-GPU=0" ]
```
**Note:** Don’t forget, after you install your docker, you need to add user to “docker” group:

```bash
$ sudo adduser `whoami` docker
```

**Note:** you likely know about the first two options `default-runtime` and `runtimes`. Be sure to include also the “unusual” option `node-generic-resources`: this is needed because the evaluation uses Docker Compose.

### 2.3. Git

We need Git and Git LFS.

On Ubuntu you can install both using

```bash
$ apt-get install git git-lfs
```

### 2.4. Duckietown Shell

Install the Duckietown Shell using:

```bash
$ pip3 install --user -U duckietown-shell
```

If you encounter problems look at *Installation* instructions in the README.

Make sure it is installed by using:

```bash
$ dts version
```

Set the `daffy` command branch:

```bash
$ dts --set-version daffy exit
```

Update the commands using:

```bash
$ dts update
```

1) **Authentication token**

Set the Duckietown authentication token using this command:

```bash
$ dts tok set
```

2) **Docker Hub information**

Set your Docker Hub username and password using:
$ dts challenges config --docker-username your username --docker-password your password

You can use an access token instead of a password.

Login to Docker Hub:

$ docker login

**Note:** Since November 2, 2020 Docker Hub has implemented tight rate limits for anonymous accounts. If you experience timeouts in Docker or similar problems, it is likely because you have not logged in recently. Note that `docker login` needs to be repeated every 12 hours.

3) Check `dts` configuration

This command checks that you have a good authentication token:

$ dts challenges info

You should expect an output like:

```
~        You are successfully authenticated:
~
~         ID: your numeric ID
~         name: your name
~         login: your account name on Duckietown
~         profile: your website
~
~         You can find the list of your submissions at the page:
~
~         https://challenges.duckietown.org/v4/humans/users/1639
```
UNIT C-3
Make your first submission

This section describes the steps to make your first submission.

**KNOWLEDGE AND ACTIVITY GRAPH**

- **Requires:** You have set up your accounts.
- **Requires:** You have the software requirement.
- **Results:** You have made a submission to the Lane Following AI-DO challenge, and you know how to try to make it better.

### 3.1. Checkout the submission repo

Check out the competition template `challenge-aido_LF-template-random`:

```bash
$ git clone https://github.com/duckietown/challenge-aido_LF-template-random
```

### 3.2. Submit

Jump into the directory:

```bash
$ cd challenge-aido_LF-template-random
```

Submit using:

```bash
$ dts challenges submit --challenge aido-hello-sim-validation
```

What this does is:
1. Build a Docker container.
2. Push the Docker container.
3. Make contact with the challenge server to send your submission.

The expected output is something along the lines of:
Sending build context to Docker daemon 5.632kB
...
Successfully created submission **SUBMISSION_NUMBER**

You can track the progress at: https://challenges.duckietown.org/v4/humans/submissions/**SUBMISSION_NUMBER**

You can also use the command:

```bash
dts challenges follow --submission **SUBMISSION_NUMBER**
```

where **SUBMISSION_NUMBER** is your submission id.

To understand more about the details of what’s happening here see Unit D-1 - Minimal pure-Python Template.

### 3.3. Monitor the submission

There are 2 ways to monitor the submission:

The first way is to use the web interface, at the URL indicated.

The second way is to use the `dts challenges follow` command:

```bash
$ dts challenges follow --submission **SUBMISSION_NUMBER**
```

### 3.4. Look at the leaderboard

The leaderboard for this challenge is available at the URL


In general all of the challenge leaderboards can be viewed at the front page the challenges website.

### 3.5. Local evaluation

You can also evaluate the submission *locally*. This is useful for debugging and development.

Use this command:

```bash
$ dts challenges evaluate --challenge aido-LF-sim-validation
```

### 3.6. Troubleshooting

If any of the commands above don’t work, it is likely that something related to Docker permissions is to blame - please file an issue, as we are trying to fix that problem.
UNIT C-4
Next steps towards winning the AI-DO

Now that you have made your first submission using the minimal template, you can now move on to the next steps.

Contents
- Section 4.1 - Understand how the minimal template works .................................................. 26
- Section 4.2 - Select the template that you need ........................................................................ 26
- Section 4.3 - Try the baselines .................................................................................................. 26
- Section 4.4 - Understand the rules ............................................................................................. 26
- Section 4.5 - Try one of the harder challenges ......................................................................... 26

4.1. Understand how the minimal template works
The anatomy of the minimal template is explained in Unit D-1 - Minimal pure-Python Template.
You will understand how the Docker infrastructure works and how to create valid submissions.

4.2. Select the template that you need
The minimal template you tried is a pure-Python template. We offer a few more templates to try if you want to use a framework.
In particular, you could try:
- the TensorFlow template;
- the PyTorch template;
- the ROS template.

4.3. Try the baselines
In Part E - Baseline Algorithms we discuss our “baselines”: submissions that do something smart.

4.4. Understand the rules
You might want to read Part B - The Challenges, which describes in detail how your score is generated for the specific challenges.

4.5. Try one of the harder challenges
In addition to the simple LF challenge you can try the multi-robot LFV challenge or the “avoid the duckies” LFP challenge.
UNIT C-5

Run an agent on your Duckiebot

In this page we will describe how to run your submission on your Duckiebot.

**KNOWLEDGE AND ACTIVITY GRAPH**

- **Requires:** You have a Duckiebot. See here for how to acquire a Duckiebot.
- **Requires:** You have built your Duckiebot.
- **Requires:** You have built your DB18 or DB19 Duckiebot.
- **Requires:** You have built your Duckietown according to the appearance specification.
- **Requires:** You can connect to your robot wirelessly.
- **Requires:** You have made a valid AI-DO submission.

**Warning:** Running your AI-DO submission on your robot is currently only supported on Ubuntu (not Mac OSX).

**Warning:** If everything’s setup right, the procedure is very straightforward. But things can be hard to troubleshoot because they involve networking.

There are two basic modes that you can use to run a submission.

1. From a local submission folder
2. From an existing image (for example one that you submitted to the AI-DO)

5.1. **Verifying that your Duckiebot is operational**

When you boot your robot it starts to produce camera imagery and wheel encoder data (if it’s moving) and waits for incoming motor commands. To verify that your Duckiebot is fully operational, you should follow Unit C-8 - Operation - Make it move and Unit C-9 - Operation - Make it see.

You should also ensure that your Duckiebot is well calibrated, both camera and wheels.

5.2. **Run a local submission on the Duckiebot**

Go into any valid submission folder (i.e. one where you could run `dts submit` and you would make a submission) and run:

```
$ dts duckiebot evaluate --duckiebot_name DUCKIEBOT_NAME
```

5.3. **Run an image that’s already built on the Duckiebot**
Run an agent on your Duckiebot

$ dts duckiebot evaluate --duckiebot_name !{DUCKIEBOT_NAME} --image IMAGE_NAME
UNIT C-6
Object Detection Dataset

6.1. Download
The dataset can be downloaded from here. We provide annotations and sample scripts for loading the annotations.

6.2. Overview
This dataset consists of 3 categories: traffic cones, duckies, and duckiebots. All of the dataset images were captured with duckiebot cameras. We use a combination of images from the Duckietown logs database and our own captured logs. Images were captured in different lighting conditions, with different versions of duckiebot models, and on different Duckietown maps. Below are some statistics and visualizations of our dataset:

<table>
<thead>
<tr>
<th>Number of images</th>
<th>1956</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of object categories</td>
<td>3</td>
</tr>
<tr>
<td>Number of objects annotated</td>
<td>5068</td>
</tr>
</tbody>
</table>

Figure 6.1
6.3. Category Details

1) Traffic Cones

<table>
<thead>
<tr>
<th>Category name</th>
<th>Cone</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of instances</td>
<td>372</td>
</tr>
<tr>
<td>Category id</td>
<td>1</td>
</tr>
</tbody>
</table>

2) Duckies

<table>
<thead>
<tr>
<th>Category name</th>
<th>Duckie</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of instances</td>
<td>2570</td>
</tr>
<tr>
<td>Category id</td>
<td>2</td>
</tr>
</tbody>
</table>

3) Duckiebots

<table>
<thead>
<tr>
<th>Category name</th>
<th>Duckiebot</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of instances</td>
<td>2126</td>
</tr>
<tr>
<td>Category id</td>
<td>3</td>
</tr>
<tr>
<td>Number of old duckiebot instances</td>
<td>1419</td>
</tr>
<tr>
<td>Number of new duckiebot instances</td>
<td>707</td>
</tr>
</tbody>
</table>

6.4. Data Loading Scripts

We provide some sample scripts for loading in the dataset here.

6.5. Data Collection Procedure

In this work, we first identify the most prominent objects that we see on the roads of Duckietown: duckies, duckiebots and traffic cones. To begin our data collection procedure, we first identify all useful logs from the Duckietown logs database which contain the objects of interest. We then download and trim these logs so that the videos consist only of frames containing our objects of interest. Finally, we convert our videos to images (frames) while skipping some number of frames between each image to ensure that we get a diverse set of images.

In these logs, there are videos of older versions of duckiebots with lots of wirings on them. However, new duckiebots are much cleaner with only the battery visible. To ensure robust detections, we needed to capture this intra-class variation. Thus, we collected our own logs containing the new duckiebots. In the final dataset, we have merged old and new duckiebots to ensure that we can detect both variations.
6.6. **Data Annotation Procedure**

We used OpenCV’s free CVAT tool to annotate the dataset.

Figure 6.3
PART D
Template Solutions

We provide a set of templates for solutions. These templates are fully functional solutions that don't do anything “smart”. They will get you a valid score on the leaderboard, but it’s unlikely that it will be very good.

Specifically, we provide the following templates:

• Minimal agent template is the most minimal feasible solution for LF* challenges,
• TensorFlow template for making a submission with a tensorflow model to the LF* challenges,
• PyTorch template for making a submission with a Pytorch model to the LF* challenges,
• ROS template for making a submission using the robot operating system to the LF* challenges,

Contents

Unit D-1 - Minimal pure-Python Template .................................................................34
Unit D-2 - ROS Template ..........................................................................................37
Unit D-3 - TensorFlow Template .............................................................................41
Unit D-4 - PyTorch Template ....................................................................................43
UNIT D-1

Minimal pure-Python Template

This section describes the contents of the simplest template: a “random” agent. It can be used as a starting point for any of the LF, LFV_multi, and LFP challenges.

**Knowledge and activity graph**

- **Requires**: That you have setup your accounts.
- **Requires**: That you meet the software requirement.
- **Results**: You make a submission to all of the LF* challenges and can view their status and output.

1.1. Quickstart

Check out the repository:

```
$ git clone github.com:duckietown/challenge-aido_LF-template-random.git
```

Change into the directory:

```
$ cd challenge-aido_LF-template-random
```

Either make a submission with:

```
$ dts challenges submit --challenge CHALLENGE_NAME
```

where you can find a list of the open challenges here.

Or, run local evaluation with:

```
$ dts challenges evaluate --challenge CHALLENGE_NAME
```

1) Verify your submission(s)

This will make a number of submissions (as described below). You can track the status of these submissions in the command line with:

```
$ dts challenges follow --submission SUBMISSION_NUMBER
```

or through your browser by navigating the webpage: https://challenges.duckietown.org/v4/humans/submissions/ SUBMISSION_NUMBER
SION_NUMBER should be replaced with the number of the submission which is reported in the terminal output.

1.2. Anatomy of the submission
The submission consists of the following files:

- submission.yaml
- Dockerfile
- Makefile
- requirements.txt
- solution.py

1) submission.yaml
The file submission.yaml contains the configuration for this submission:

```yaml
challenge: [c1,c2]
protocol: aido2_db18_agent-z2
user-label: random_agent
user-payload:
```

- With challenge you can list the challenges that you want your submission to be run on.
- The user-label can be changed to your liking
- The protocol and user-payload should probably be left as they are.

2) requirements.txt
This file contains any python requirements that are needed by your code.

3) solution.py
The solution.py solution file illustrates the protocol interface.

The important parts are:

```python
def on_received_observations(self, data: DB20Observations):
camera: JPGImage = data.camera
odometry = data.odometry
_rgb = jpg2rgb(camera.jpg_data)
```

which reads an image whenever one becomes available, and
def on_received_get_commands(self, context: Context):
    if self.n == 0:
        pwm_left = 0.0
        pwm_right = 0.0
    else:
        pwm_left = np.random.uniform(0.5, 1.0)
        pwm_right = np.random.uniform(0.5, 1.0)
    self.n += 1

    # pwm_left = 1.0
    # pwm_right = 1.0
    grey = RGB(0.0, 0.0, 0.0)
    led_commands = LEDSCommands(grey, grey, grey, grey, grey)
    pwm_commands = PWMCommands(motor_left=pwm_left, motor_right=pwm_right)
    commands = DB20Commands(pwm_commands, led_commands)
    context.write('commands', commands)

which asks for wheel commands to be sent to the robot. Your code must finish by sending the commands to the robot with the context.write command.
This section describes the basic procedure for making a submission with a model trained in using the Robot Operating System. It can be used as a starting point for any of the LF, LFV_multi, and LFP challenges.

**Knowledge and activity graph**

| Requires: | That you have setup your accounts. |
| Requires: | That you meet the software requirement. |
| Requires: | That you have a basic understanding of ROS. |
| Results: | You make a submission to all of the LF* challenges and can view their status and output. |

### 2.1. Quickstart

Clone the template repo:

```
$ git clone git@github.com:duckietown/challenge-aido_LF-template-ros.git
```

Change into the directory:

```
$ cd challenge-aido-LF-template-ros
```

Either make a submission with:

```
$ dts challenges submit --challenge CHALLENGE_NAME
```

where you can find a list of the open challenges here.

Or, run local evaluation with:

```
$ dts challenges evaluate --challenge CHALLENGE_NAME
```

1) Verify the submission:

This will make a number of submissions (as described below). You can track the status of these submissions in the command line with:

```
$ dts challenges follow --submission SUBMISSION_NUMBER
```

or through your browser by navigating the webpage: https://challenges.ducki-
etown.org/v4/humans/submissions/ SUBMISSION_NUMBER

where SUBMISSION_NUMBER should be replaced with the number of the submission which is reported in the terminal output.

2.2. Anatomy of the submission

The submission consists of all of the basic files that required for a basic submission. Below we will highlight the specifics with respect to this template.

There are also a few other new files and folders in this submission:

```
launchers/
rosagent.py
submission_ws/
```

and additionally the solution.py and Dockerfile have changed. We will describe each of these in detail.

**Note:** If you don’t care about the details, or just want to get started, you can start by adding new ROS packages into the submission_ws.

1) Dockerfile

The main update here is that we build your catkin workspace inside (the submission_ws folder) in the Dockerfile:

```
RUN . /opt/ros/${ROS_DISTRO}/setup.sh && . ${CATKIN_WS_DIR}/devel/setup.bash &&
catkin build --workspace /code/submission_ws
```

Also note that instead of just running solution.py when we enter the container, we now run a “launcher” (in the launchers folder) called run_and_start.sh. For details see Subsection 2.2.4 - launchers/

Also note that in this Dockerfile we are not copying the entire directory over, instead we are copying files individually (this is actually more efficient). So if you add new files that you are using that are outside of the submission_ws and launchers folders, you will have to add additional COPY commands.

2) solution.py

**You probably don’t need to change this file.**

We instantiate a ROSAgent() (see Subsection 2.2.3 - rosagent.py) and this becomes the object that handles interfacing with the ROS interface. This includes the publishing of imagery and encoder data to ROS:
and the setting of actions and LEDs:

```python
pwm_left, pwm_right = self.agent.action
pwm_commands = PWMCommands(motor_left=pwm_left, motor_right=pwm_right)
led_commands = LEDSCommands(grey, grey, grey, grey, grey, grey)
commands = DB20Commands(pwm_commands, led_commands)
```

3) **rosagent.py**

You probably don’t need to change this file.

`rosagent.py` sets up a class that can be used to interface with the rest of the ROS stack. It is for all intents and purposes a fully functional ROS node except that it isn’t launched through ROS, it is instantiated in code. This class takes care of a few useful things, such as getting the correct camera calibration files, subscribing to control commands and sending them to your robot (real or simulated), as well as retrieving the sensor data from the robot and publishing it to ROS.

The main functions are:

- `_publish_img(self, obs)`, which takes the camera observation from the environment, and publishes it to the topic that you specify in the constructor of the ROSAgent.
- `_publish_odometry(self, resolution_rad, left_rad, right_rad)`, which takes the encoder data from the robot, and publishes it to the topic specified in the constructor of the ROSAgent.
- `_ik_action_cb(msg)`, listens on the inverse kinematics action topic, and assigns it to `self.action`.

4) **launchers/**

The bash scripts in the `launchers` directory are there to help you get everything started when you run your container. In this template there is only `run_and_start.sh`: 
#!/bin/bash

roscore &
source /environment.sh
source /opt/ros/noetic/setup.bash
source /code/catkin_ws/devel/setup.bash
source /code/submission_ws/devel/setup.bash
python3 solution.py &

You are free to modify this as you see fit, but a few things are important to consider.

1. The order that we `source` things matters. If we have a package with the same name in two workspaces, ROS will run whichever one got sourced last.

2. If you don’t put things in the background (with &) then if those commands don’t end, subsequent commands will not get run.

3. The `--wait` flag in the `roslaunch` command is recommended so that `roslaunch` will wait until the `roscare` has finished initializing.

5) `submission_ws/`

This is a standard ROS catkin workspace. You can populate it with ROS packages. You will notice that the `random_action` package is already in the workspace. This can be used as a template for creating more packages. The main elements are launch files in the `launch` folder (you will see the `random_action_node.launch` which is launched by the `run_and_start.sh` launcher), the `src` folder which contains the ROS nodes, and the `include` folder which contains your python includes (you can also write nodes in C++ or other languages if you prefer).
UNIT D-3
TensorFlow Template

This section describes the basic procedure for making a submission with a model trained in using TensorFlow. It can be used as a starting point for any of the LF, LFV_multi, and LFP challenges.

**KNOWLEDGE AND ACTIVITY GRAPH**

**Requires:** That you have setup your accounts.

**Requires:** That you meet the software requirement.

**Results:** You make a submission to all of the LF* challenges and can view their status and output.

### 3.1. Quickstart

Clone the template repo:

```bash
$ git clone git@github.com:duckietown/challenge-aido_LF-template-tensorflow.git
```

Change into the directory:

```bash
$ cd challenge-aido_LF-template-tensorflow
```

Either make a submission with:

```bash
$ dts challenges submit --challenge "CHALLENGE_NAME"
```

where you can find a list of the open challenges here.

Or, run local evaluation with:

```bash
$ dts challenges evaluate --challenge "CHALLENGE_NAME"
```

1) Verify your submission(s)

This will make a number of submissions (as described below). You can track the status of these submissions in the command line with:

```bash
$ dts challenges follow --submission "SUBMISSION_NUMBER"
```

or through your browser by navigating the webpage: https://challenges.duckietown.org/v4/humans/submissions/ "SUBMISSION_NUMBER"
where **SUBMISSION_NUMBER** should be replaced with the number of the submission which is reported in the terminal output.

### 3.2. Anatomy of the submission

The submission consists of all of the basic files that required for a basic submission. Below we will highlight the specifics with respect to this template.

1) **solution.py**

The only difference in **solution.py** is that we are initializing our model:

```python
from model import TfInference

self.model = TfInference(  # define observation and output shapes
    observation_shape=(1,) + expect_shape,
    # this is the shape of the image we get.
    action_shape=(1, 2),  # we need to output v, omega.
    graph_location='tf_models/'  # this is the folder where our models are stored.
)

self.current_image = np.zeros(expect_shape)
```

and then we call our model to compute an action with the following code:

```python
def compute_action(self, observation):
    action = self.model.predict(observation)
    return action.astype(float)
```

Note that we also can require the presence of a GPU with the environment variable `AI-DO_REQUIRE_GPU` and then the solution will fail if a GPU is not found.

2) **Model files**

The other additional files are the following:

**tf_models/**

**model.py**

The directory `tf_models/` contains the Tensorflow learned models (the ones that you have trained).

The `model.py` code is the code that runs the Tensorflow model.
This section describes the basic procedure for making a submission with a model trained in using PyTorch. It can be used as a starting point for any of the LF, LFV_multi, and LFP challenges.

**Knowledge and Activity Graph**

- **Requires:** That you have setup your accounts.
- **Requires:** That you meet the software requirement.
- **Results:** You make a submission to all of the LF* challenges and can view their status and output.

### 4.1. Quickstart

Clone the template repo:

```
$ git clone git://github.com/duckietown/challenge-aido_LF-template-pytorch.git
```

Change into the directory:

```
$ cd challenge-aido_LF-template-pytorch
```

Run the submission:

Either make a submission with:

```
$ dts challenges submit --challenge CHALLENGE_NAME
```

where you can find a list of the open challenges here.

Or, run local evaluation with:

```
$ dts challenges evaluate --challenge CHALLENGE_NAME
```

1) **Verify the submission(s)**

This will make a number of submissions (as described below). You can track the status of these submissions in the command line with:

```
$ dts challenges follow --submission SUBMISSION_NUMBER
```
or through your browser by navigating the webpage: https://challenges.duckietown.org/v4/humans/submissions/ SUBMISSION_NUMBER
where SUBMISSION_NUMBER should be replaced with the number of the submission which is reported in the terminal output.

4.2. Anatomy of the submission

The submission consists of all of the basic files that required for a basic submission. Below we will highlight the specifics with respect to this template.

1) solution.py

The only differences in solution.py (the python script that is run by our submission) are:

- We conditionally load the model in the initialization procedure:

```python
self.model = DDPG(state_dim=self.preprocessor.shape, action_dim=2,
                   max_action=1, net_type="cnn")
self.current_image = np.zeros((640, 480, 3))
```

```python
if load_model:
    logger.info('PytorchRLTemplateAgent loading models')
    fp = model_path if model_path else "model"
    self.model.load(fp, "models", for_inference=True)
```

- We abort if no GPU is detected and the environment variable AIDO_REQUIRE_GPU.
- We are calling our model to compute an action with the following code:

```python
def compute_action(self, observation):
    action = self.model.predict(observation)
    return action.astype(float)
```

4.3. Model files

The other addition files are the following:

wrappers.py
model.py
models

wrappers.py contains a simple wrapper for resizing the input image. model.py is used for training the model, and the models are stored in models.
To help competitors get started, we have implemented some baseline algorithms. These can be built on or used for inspiration. At present, all of these baseline algorithms are for the LF* challenges:

- Classical Duckietown stack,
- Dataset aggregation from simulation (with PyTorch),
- Reinforcement learning (with PyTorch),
- Residual Policy learning (with PyTorch).

Contents

Unit E-1 - Duckietown Baseline

Unit E-2 - Reinforcement Learning

Unit E-3 - Dataset Aggregation

Unit E-4 - Behavior Cloning

Unit E-5 - Residual Policy Learning
UNIT E-1

Duckietown Baseline

This section describes the basic procedure for making a submission using the Robot Operating System and the Duckietown software stack.

**Knowledge and activity graph**

| Requires: | That you have made a submission with the ROS template and you understand how it works. |
| Requires: | You already know something about ROS. |
| Results:  | You have a competitive submission. |

### 1.1. Quickstart

Clone this repo

```
$ git clone git@github.com/duckietown/challenge-aido_LF-baseline-duckietown.git
```

Change into the directory:

```
$ cd challenge-aido_LF-baseline-duckietown
```

Test the submission, either locally with:

```
$ dts challenges evaluate --challenge \[CHALLENGE_NAME\]
```

or make an official submission when you are ready with

```
$ dts challenges submit --challenge \[CHALLENGE_NAME\]
```

You can find the list of challenges here. Make sure that it is marked as “Open”.

### 1.2. Baseline Details

The “Duckietown” baseline is based on the ROS template.

1) Dockerfile

One important facet of the Dockerfile is that we use a “multi-stage build”:
This allows us to take some elements from each of the first two base images, and copy them into the `dt-core` image:

```dockerfile
COPY --from=dt-car-interface ${CATKIN_WS_DIR}/src/dt-car-interface
COPY --from=template /data/config /data/config
COPY --from=template /code/rosagent.py .
```

As a result, we have the calibration files (from `/data/config`) as well as the `rosagent.py` from the `challenge-aido_lf-template-ros` and all of the source files from the `dt-car-interface` image.

We also get everything that is in the `dt-core` image.

The remainder of the Dockerfile is very similar to the Dockerfile in the ROS template.

2) `solution.py`

The `solution.py` has no changes compared to the ROS template. It is duplicated here for clarity, in the event that you wanted to, for example change the launcher that was run in the final `CMD` line.

3) `launchers/`

There is only one “launcher”, and it deviates slightly from the one in the ROS template:

```bash
#!/bin/bash
roscore
source /environment.sh
source /opt/ros/noetic/setup.bash
source /code/catkin_ws/devel/setup.bash
source /code/submission_ws/devel/setup.bash
python3 solution.py
roslaunch --wait car_interface all.launch veh:=${VEHICLE_NAME}
roslaunch --wait duckietown_demos lane_following.launch
sleep 5
rostopic pub /${VEHICLE_NAME}/fsm_node/mode duckietown_msgs/FSMState '{header: , state: "LANE_FOLLOWING"}'}
```

Here we launch the `lane_following.launch` launch file from the `duckietown_demos` package. We don’t go into the intricate details of everything that is run in this launch
file here, but some of the more consequential nodes which are getting launched are the following:

- **line_detector_node**: Used to detect the lines in the image.
- **ground_projection_node**: Used to project the lines onto the ground plane using the camera extrinsic calibration.
- **lane_filter_node**: Used to take the ground projected line segments and estimate the Duckiebot's position and orientation in the lane.
- **lane_controller_node**: Used to take the estimate of the robot and generate a reference linear and angular velocities for the Duckiebot.

4) submission_ws/

The submission_ws folder contains all of the new ROS packages that you would like to include in your submission. It is currently empty, but there is a reference package included in the ROS template.

勃Note: Importantly, your submissions_ws is sourced after the existing catkin_ws that is included in dt-core. As a result, if you include a node and package in your submission_ws with the same name as one in dt-core, the one in submission_ws will get executed. This is convenient because it means that, as long as you adhere to the same subscriptions and publications, you don’t need to define any new launch file, lane_following.launch will automatically launch your newly written node.

1.3. Local Development Workflow

For rapid local development, you can make use of the dts exercises API, developed to build and test exercises and assignments in class settings.

1) Building your Code

From inside the challenge-aido_LF-baseline-duckietown folder, you can start by building your code with:

```
$ dts exercises build
```

This performs catkin build inside a docker container. If you go inside the submission_ws folder you will notice that there are more folders that weren’t there before. These are build artifacts that persist from the building procedure because of mounting.

2) Running in Simulation

You can run your current solution in the gym simulator with:

```
$ dts exercises test --sim
```

Then you can look at what’s happening by looking through the browser at http://localhost:8087. Open up the rqt_image_view, resize it, and choose /agent/camera_node/
image/compressed in the dropdown. You should see the image from the robot in the simulator.

You might want to launch a virtual joystick by opening a terminal and doing:

```bash
$ dt-launcher-joystick
```

By default the duckiebot is in joystick control mode, so you can freely drive it around. You can also set it to LANE FOLLOWING mode by pushing the a button when you have the virtual joystick active. If you do so you will see the robot move forward slowly and never turn.

3) Testing Your Algorithm on the Robot

If you are using a Linux laptop, you have two options, local (i.e., on your laptop) and remote (i.e., on the Duckiebot). To run “locally”

```bash
$ dts exercises test --duckiebot_name ROBOT_NAME --local
```

To run on the Duckiebot:

```bash
$ dts exercises test --duckiebot_name ROBOT_NAME
```

In both cases you should still be able to look at things through novnc by pointing your browser to http://localhost:8087. If you are running on Linux, you can load up the virtual joystick and start lane following as above.

**Warning:** If you are Mac user unfortunately you should not use the --local flag

### Starting Lane Following on Mac:

Since we can’t publish from Mac and have it be received by ROS, we have to do something slightly different. In a new terminal on your Mac do:

```bash
$ docker -H ROBOT_NAME.local exec agent launchers/start_lane_following.sh
```

This will run the start_lane_following.sh bash script inside the agent container which initiates LANE_FOLLOWING mode.

Similarly, you can stop your Duckiebot from lane following by doing:

```bash
$ docker -H ROBOT_NAME.local exec agent launchers/stop_lane_following.sh
```

You could also do an equivalent thing through the Portainer interface in the dashboard by opening a new terminal in your agent container and running the corresponding launcher.
4) How to Improve your Submission

A good way to get started could be to copy one of the packages defined in the Duckietown dt-core repo or the Duckietown dt-car-interface repo into the submission_ws folder and modify it. Note that your modified package will automatically get run because of the order of the sourcing of the catkin workspaces in the run_and_start.sh launch file.

If you would like to add a new package and node that includes a functionality not already run by lane_following.launch or you would like to change the connectivity of interfaces of these nodes, then you will also need:

- to write your own launch file that launches your node and also all of the other nodes from the base images that you would still like to use.
- to modify the launch file run_and_start.sh so that it launches your newly created launchfile. You could equally define a new launchfile, but then make sure that it gets executed in the last line of your Dockerfile.

5) Other Possibly Useful Utilities

All of the normal ROS debugging utilities are available to you through the novnc desktop. For example, You might also explore the other outputs that you can look at in rqt_image_view.

Also useful are some debugging outputs that are published and visualized in RViz. You can open RViz through the terminal in the novnc desktop by typing:

```
$ rviz
```

In the window that opens click “Add” the switch to the topic tab, then find the segment_markers, and you should see the projected segments appear. Do the same for the pose_markers.

Another tool that may be useful is rqt_plot which also can be opened through the terminal in novnc. This opens a window where you can add “Topics” in the text box at the top left and then you will see the data get plotted live.

All of this data can be viewed as data through the command line also. Take a look at all of the rostopic command line utilities.
This section describes the basic procedure for making a submission with a model trained in simulation using reinforcement learning with PyTorch.

**Knowledge and activity graph**

- **Requires:** That you have made a submission with the PyTorch template.
- **Requires:** You should install CUDA10.2+ locally. This baseline works with CUDA 11, and it should also work with CUDA 10.2.
- **Requires:** Patience, training RL agents is not easy
- **Results:** You have a functional agent trained with RL. Your expectations in regards to end-to-end RL’s capabilities should be realistic.

Before getting started, you should be aware that RL is very much an active area of research. Simply getting a successful turn with this baseline should be celebrated. It is still provided to you because this implementation is a good stepping point to other algorithms. We also assume here that you are relatively familiar with the basics of reinforcement learning. There are many tutorials and resources, and even complete courses, online for learning about RL, but for a succinct introduction, you can check out the Reinforcement Learning lecture from the IFT6757 class at the University of Montreal, or try our reinforcement learning Jupyter notebook which is in the Duckietown exercises repository.

You should also make sure you have access to good hardware. A recent graphics card (probably GTX1060+) is a must, and more than 8GB of RAM is required.

**2.1. Quickstart**

Clone this repo

```
$ git clone git@github.com/duckietown/challenge-aido_LF-baseline-sim-pytorch.git
```

Change into the directory:

```
$ cd challenge-aido_LF-baseline-sim-pytorch
```

Test the submission, either locally with:

```
$ dts challenges evaluate --challenge [CHALLENGE_NAME]
```

or make an official submission when you are ready with
You can find the list of challenges here. Make sure that it is marked as “Open”.

2.2. How to Train your Policy

The previous uses the model that is included in the baseline repository. You are going to want to train your own policy.

To do so:

Change into the directory:

```
$ cd challenge-aido_LF-baseline-RL-sim-pytorch
```

Install this package:

```
$ pip3 install -e .
```

and the `gym-duckietown` package:

```
$ pip3 install -e git://github.com/duckietown/gym-duckietown.git@daffy#egg=gym-duckietown
```

**Note:** Depending on your configuration, you might need to use pip instead of pip3

Change into the `duckietown_rl` directory and run the training script

```
$ cd duckietown_rl
$ python3 -m scripts.train_cnn.py --seed 123
```

When it finishes, try it out (make sure you pass in the same seed as the one passed to the training script)

```
$ python3 -m scripts.test_cnn.py --seed 123
```

2.3. How to submit the trained policy

Once you’re done training, you need to copy your model and the saved weights of the policy network.

Specifically if you use this repo then you need to copy the following artifacts into the corresponding locations of the root directory:

- `duckietown_rl/ddpg.py` and rename to `model.py`
- `scripts/pytorch_models/DDPG_XXX_actor.pth` and `DDPG_XXX_critic.pth` and rename to `models/model_actor.pth` and `models/model_critic.pth` respectively, where
XXX is the seed of your best policy

Also, make sure that the root-level wrappers.py contains all the wrappers you used in duckietown_rl/wrappers.py.

Then edit the solution.py file over to make sure everything is loaded correctly (i.e. all of the imports point to the right place).

Finally, you evaluate or submit your agent using the process described above in the Quickstart.

2.4. How to improve your policy

Here are some ideas for improving your policy:

- Check out the DtRewardWrapper and modify the rewards (set them higher or lower and see what happens)
- Try resizing the images. Make them smaller to speed up training, or bigger for ensuring that your RL agent can extract everything it can from them. You will need to also edit the layers in ddpg.py accordingly.
- Try making the observation image grayscale instead of color.
- Try stacking multiple images, like 4 monochrome images instead of 1 color image. You will need to also edit the layers in ddpg.py accordingly.
- You can also try increasing the contrast in the input to make the difference between road and road-signs clearer. You can do so by adding another observation wrapper.
- Cut off the horizon from the image (and correspondingly change the convnet parameters).
- Check out the default hyperparameters in duckietown_rl/args.py and tune them. For example increase the expl_noise or increase the start_timesteps to get better exploration.
- (more sophisticated) Use a different map in the simulator, or - even better - use randomized maps. But be mindful that some maps include obstacles on the road, which might be counter-productive to a LF submission.
- (more advanced) Use a different/bigger convnet for your actor/critic. And add better initialization.
- (very advanced) Use the ground truth from the simulator to construct a better reward.
- (extremely advanced) Use an entirely different training algorithm - like PPO, A2C, or DQN. But this might take significant time, even if you’re familiar with the matter.

2.5. Sim2Real Transfer (Optional)

You should try your agent on the real Duckiebot.

It is possible, even likely, that your agent will not generalize well to the real environment. One approach to mitigate this problem is to randomize the simulator environment during training, in the hope that this improves generalization. This approach is referred to as “Domain Randomization”.

To implement this, you will need to modify the `env.py` file. You’ll notice that we launch the `Simulator` class from `gym-duckietown`. When we take a look at the constructor, you’ll notice that we aren’t using all of the parameters listed. In particular, the three you should focus on are:

- `map_name`: What map to use; hint, take a look at `gym_duckietown/maps` for more choices
- `domain_rand`: Applies domain randomization, a popular, black-box, sim2real technique
- `randomized_maps_on_reset`: Slows training time, but increases training variety.

Mixing and matching different values for these will help you improve your training diversity, and thereby improving your evaluation robustness.

If you’re interested in more advanced techniques, like learning a representation that is a bit easier for your network to work with, or one that transfers better across the simulation-to-reality gap, there are some alternative, more advanced methods you may be interested in trying out.

### 2.6. Training headless

Should you want to train on a server, you will notice that the simulator requires an X server to run. Fear not, however, as we can use a fake X server for it.

```
$ xvfb-run -s "-screen 0 1400x900x24" python3 -m scripts.train_cnn.py --seed 123
```

That way, we trick the simulator into thinking that an X server is running. And, to be honest, from its point of view, it’s actually true!

### 2.7. Controlling which GPU is being used

Your machine might have more than one GPU. To select the nth instead of the 0th, you can use

```
$ CUDA_VISIBLE_DEVICES=n python3 -m scripts.train_cnn.py --seed 123
```

This is, of course, combinable with running on a server

```
$ CUDA_VISIBLE_DEVICES=n xvfb-run -s "-screen 0 1400x900x24" python3 -m scripts.train_cnn.py --seed 123
```
This section describes the procedure for training and testing an agent with the gym-duckietown simulator using the Dagger algorithm. It can be used as a starting point for any of the LF, LFP, and LFV_multi challenges.

**Knowledge and Activity Graph**

<table>
<thead>
<tr>
<th>Requires:</th>
<th>You are somewhat familiar with PyTorch and the Pytorch template.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Results:</td>
<td>You could win the AI-DO!</td>
</tr>
</tbody>
</table>

### 3.1. Introduction

We saw a first implementation of imitation learning in the behaviour cloning baseline. That baseline models the driving task as an end-to-end supervised learning problem where data can be collected offline from an expert. One of the central issues with this approach is that of **distributional shift**. Since this is a sequential decision making problem, the training data are not “identically and independently distributed”. The result is that if your agent deviates from the **optimal** trajectory that was demonstrated by the expert, it will not have any data in its dataset that shows it how to **recover** back to the optimal trajectory. As a result, it is unlikely that the behaviour cloning approach will be robust.

For a better result than behaviour cloning this second version of imitation learning does not train only on a single trajectory given by the expert. We follow the Dataset Aggregation algorithm (Dagger) where we also let the agent interact with the environment and allow the expert to **recover**. The actions between the expert and the learner are chosen randomly with a varying probability with the hope that the expert **corrects** the learner if it starts deviating from the optimal trajectory.

### 3.2. Quickstart

Clone this repo:

```
$ git clone https://github.com/duckietown/challenge-aido_LF-baseline-dagger-pytorch.git
```

Change into the directory:

```
$ cd challenge-aido_LF-baseline-dagger-pytorch
```

In here you will see two directories submission and learning. To make a submission, enter the submission folder:
Then test the submission, either locally with:

```bash
$ dts challenges evaluate --challenge CHALLENGE_NAME
```

or make an official submission when you are ready with

```bash
$ dts challenges submit CHALLENGE_NAME
```

You can find the list of challenges here. Make sure that it is marked as “Open”.

### 3.3. Local Development Workflow

The previous submission used a model which is included in the repo, but you should try to improve upon it.

1) **Option 1: Training with Collab**

We provide a Collab notebook that you can used to get started.

During training the loss curve for each episode is available (by default on a folder created on root called `iil_baseline`) and may be checked using `tensorboard` and specifying the `--logdir`. On the same folder you will have `data.dat` and `target.dat` which are the memory maps used by the dataset.

2) **Option 2: Training Locally**

Start by cloning the gym-duckietown simulator repo:

```bash
$ git clone https://github.com/duckietown/gym-duckietown.git
```

Change into the directory:

```bash
$ cd gym-duckietown
```

Install the package:

```bash
$ pip3 install -e .
```

To run the baseline training procedure, run:

```bash
$ python -m learning.train
```

in the root directory.
3) Parameters that can affect training

There are several optional flags that may be used to modify hyperparameters of the algorithm:

- **--episode or -i** an integer specifying the number of episodes to train the agent, defaults to 10.
- **--horizon or -r** an integer specifying the length of the horizon in each episode, defaults to 64.
- **--learning-rate or -l** integer specifying the index from the list [1e-1, 1e-2, 1e-3, 1e-4, 1e-5] to select the learning rate, defaults to 2.
- **--decay or -d** integer specifying the index from the list [0.5, 0.6, 0.7, 0.8, 0.85, 0.9, 0.95] to select the initial probability to choose the teacher, the learner.
- **--save-path or -s** string specifying the path where to save the trained model, models will be overwritten to keep latest episode, defaults to a file named iil_baseline.pt on the project root.
- **--map-name or -m** string specifying which map to use for training, defaults to loop_empty.
- **--num-outputs** integer specifying the number of outputs the model will have, can be modified to train only angular speed, defaults to 2 for both linear and angular speed.
- **--domain-rand or -dr** a flag to enable domain randomization for the transferability to real world from simulation.
- **--randomize-map or -rm** a flag to randomize training maps on reset.

The baseline model is based on the Dronet model. The feature extractor of the model is frozen while the classifier is modified for the regression task.

All the PyTorch boilerplate code is encapsulated in the `NeuralNetworkPolicy` class implemented on `learning/imitation/iil-dagger/learner/neural_network_policy.py` and is based on previous work done by Manfred Díaz on Tensorflow.

4) Local Evaluation

A simple testing script `test.py` is provided with this implementation. It loads the latest model from the provided directory and runs it on the simulator. To test the model:

```
$ python -m learning.test --model-path path
```

The model path flag has to be provided for the script to load the model:

- **--model-path or -mp** string specifying the path to the saved model to be used in testing.

Other optional flags that may be used are:

- **--episode or -i** an integer specifying the number of episodes to test the agent, defaults to 10.
- **--horizon or -r** an integer specifying the length of the horizon in each episode, defaults to 64.
• \texttt{--save-path} or \texttt{--s} string specifying the path where to save the trained model, models will be overwritten to keep latest episode, defaults to a file named \texttt{iil_baseline.pt} on the project root.
• \texttt{--num-outputs} integer specifying the number of outputs the model has, defaults to 2.
• \texttt{--map-name} or \texttt{--m} string specifying which map to use for training, defaults to \texttt{loop_empty}.

5) Expected Results

The following video shows the results for training the agent during 130 episodes and keeping the rest of the configuration to its default:

![Training a duckybot agent interactively in duckietown gym](image)

Figure 3.1

6) Tips to Improve your model

Some ideas on how to improve on the provided baseline:
• Map randomization.
• Domain randomization.
• Better selection than random when switching between expert/learner actions.
• Balancing the loss between going straight and turning.
• Change the task from linear and angular speed to left and right wheel velocities.
• Improving the teacher.

3.4. References
UNIT E-4

Behavior Cloning

In this part, you can find all the required steps in order to make a submission based on Behavior Cloning with Tensorflow for the lane following task using data varying from real data or simulator data. It can be used as a strong starting point for any of the challenges.

**KNOWLEDGE AND ACTIVITY GRAPH**

- **Requires:** That you have made a submission with the tensorflow template.
- **Results:** You win the AI-DO!

### 4.1. Introduction

This baseline refers to Nvidia’s approach for behavior cloning for autonomous vehicles. You can find the original paper here: End to End Learning for Self-Driving Cars. It is created by Frank (Chude Qian) for his submission to AIDO3 in NeurIPS 2019. The submission was very successful on simulator challenge, however, it was not the best for realworld challenges. I have decided to opensource this submission as a baseline to inspire better results. A detailed description on the specific implementation for this baseline can be found on the summary poster here: Teaching Cars to Drive Themselves. Additional reference can also be found on the summary poster.

### 4.2. Quickstart

Clone the baseline Behavior Cloning repository:

```
$ git clone -b daffy https://github.com/duckietown/challenge-aido_LF-baseline-behavior-cloning.git
$ cd challenge-aido_LF-baseline-behavior-cloning
```

The code you find is structured into 5 folders.

1. Teach your duckiebot to drive itself in `duckieSchool`.
2. *(Optional)* Store all the logs that can be used for training using `duckieLog`.
3. Train your model using tensorflow in `duckieTrainer`.
4. *(Optional)* Hold all previous models you generated in `duckieModels` in case you need it.
5. Submit your submission via `duckieChallenger` folder.

### 4.3. The duckieSchool
In this folder you will find two types of duckieSchool: simulator based duckieGym and real robot based duckieRoad.

1) Installing duckietown Gym

To install duckietown Gym and all the necessary dependencies:

```bash
pip3 install --use-feature=2020-resolver -r requirements.txt
```

2) Use joystick to drive

Before you use the script, make sure you have the joystick connected to your computer. To run the script, use the following command:

```bash
$ python3 human.py
```

The system utilizes an Xbox One S joystick to drive around. Left up and down controls the speed and right stick left and right controls the velocity. Right trigger enables the “DRS” mode allows vehicle to drive full speed forward. (Note there are no angular acceleration when this mode is enabled).

In addition, every 1500 steps in simulator, the recording will pause and playback. You will have the chance to review the result and decide whether to keep the log or not. The log are recorded into two formats: raw_log saves all the raw information for future reprocessing, and training_data saves the directly feedable log.

3) Options for joystick script

For driving duckiebot with a joystick in a simulator, you have the following options:

1. **--env-name**: currently the default is None.
2. **--map-name**: This sets the map you choose to run. Currently it is set as small_loop_cw.
3. **--draw-curve**: This draw the lane following curve. Defaultly it is set as False. However, if you are new to the system, you should familiarize yourself with enabling this option as True.
4. **--draw-bbox**: This helps draw out the collision detection bounding boxes. Defaultly it is set as False.
5. **--domain-rand**: This enables domain randomization. Defaultly it is set as True.
6. **--playback**: This enables playback after each record section for you to inspect the log you just took. Defaultly it is set as True.
7. **--distortion**: This enables distortion to let the view as fisheye lens. Defaultly it is set as True.
8. **--raw_log**: This enables recording also a high resolution version of the log instead of the downsampled version. Defaultly it is set as True. **Note: if you disable this option, playback will be disabled too.**
9. **--steps**: This sets how many steps to record once. Defaultly it is set as 1500.

---

**Behavior Cloning**

61
10. **--nb-episodes**: This controls how many episodes (aka sessions) you drive. This value typically don’t matter as you will probably get tired before this value reaches.

11. **--logfile**: This specifies where you can store your log file. Defaultly it will just save the log file at the current folder.

12. **--downscale**: This option currently is disabled.

13. **--filter-bad-data**: This option allows you to only logs driving better than last state. It uses reward feedback on the duckietown gym for tracking the reward status. Additionally, some other features has been hard coded:

1. Currently the training image are stored as YUV color space, you can change it in line 258.
2. Currently the frame is sized as 150x200 per Nvidia’s recommendation. This could be not the most effective resolution.
3. Currently the logger resets if it detects you drive out of the bound.

**4) Automated log generation using pure pursuit**

In this year, we also provide you with an option to automatically generate training sample using the concept of pure pursuit method. For more information, you can check out this video

The configurables are pretty much the same as the human driver agent.

If you would like to mass generate training samples on a headless server, under util folder you can find the tools for that.

To start pure pursuit data generation:

```
$ python3 automatic.py
```

**5) Log using an actual duckiebot**

To log using an actual duckiebot, refer to this tutorial on how to get a rosbag on a duckiebot.

Once you have obtained the ROS bag, you can use the folder `duckieRoad` to process that log.

**6) Process a log from an actual duckiebot**

You will find the following files in the `duckieRoad` directory.
Dockerfile                      # File that sets up the docker image
├── bag_files                       # Put your ROS bags here.
│   ├── ROSBAG1                     # Your ROS bag.
│   ├── ROSBAG2                     # Your training on Date 2.
│   └── ...
├── converted                       # Stores the converted log for you
to train the duckiebot
├── src                             # Scripts to convert ROS bag to
pickle log
│   ├── _loggers.py                 # Logger used to log the pickle log
│   ├── extract_data_functions.py   # Helper function for the script
│   └── extract_data.py             # Conversion script. You set your
duckiebot
    name, and topic to convert here.
├── MakeFile                        # Make file.
├── requirements.txt                # Used for docker to setup dependen-
cy
└── pickle23.py                     # Convert the pickle2 style log pro-
duced to pickle 3

https://docs.duckietown.org/daffy/duckietown-robotics-development/out/ros_logs.html

You should change extract_data.py line 83 to the correct VEHICLE_NAME.

First put your ROS bags in the bag_files folder. Then:

```
$ make make_extract_container
```

Next start the conversion docker:

```
$ make start_extract_data
```

It will automatically mount the bags folder as well as the converted folder.

NOTE: When you run the make file, make sure you are in duckieRoad not in the src
folder!

4.4. The duckieLog

This folder is set for your to put all of your duckie logs. Some helper functions are pro-
vided. However, they might not be the most efficient ones to run. It is here for your reference.
1) The log viewer

To view the logs, under duckieLog folder:

```
$ python3 util/log_viewer.py --log_name YOUR_LOG_FILE_NAME.log
```

2) The log combiner

To combine the logs, under duckieLog folder:

```
$ python3 util/log_combiner.py --log1 dataset1.log --log2 dataset2.log
    --output newdataset.log
```

4.5. The duckieTrainer

This section describes everything you need to know using the duckieChallenger.

1) Folder structure

In this folder you can find the following files:

```
├── __pycache__                     # Python Compile stuff.
│   ├── trainlogs                            # Training logs for tfboard.
│       ├── Date 1                      # Your training on Date 1.
│       ├── Date 2                      # Your training on Date 2.
│       └── ...
│   └── trainedModel                    # Your trained model is here.
│       ├── FrankNetBest_Loss.h5        # Lowest training loss model.
│       ├── FrankNetBest_Validation.h5  # Lowest validation loss model.
│       └── FrankNet.h5                 # The last model of the training.
│   └── frankModel.py                   # The deep learning model.
├── logReader.py                    # Helper file for reading the log
├── train.py                        # The training setup.
├── requirements.txt                # Required pip3 packages for training
└── train.log                       # Your training data.
```

2) Environment Setup

To setup your environment, I strongly urge you to train the model using a system with GPU. Tensorflow and GPU sometimes can be confusing, and I recommend you to refer to tensorflow documentation for detailed information.

Currently, the system requires TensorFlow 2.2.1. To setup TensorFlow, you can refer to the official TensorFlow install guide here.

Additionally, this training system utilizes scikit-learn and numpy. You can find a provided requirements.txt file that helps you install all the necessary packages.
3) Model Adjustment

To change the model, you can modify the `frankModel.py` file as it includes the model architecture. Currently it uses a parallel architecture to separately generate a linear and angular velocity. It might perform better if they are not setup separately.

To change your training parameters, you can find EPOCHS, LEARNING RATE, and BATCH size at the beginning of `train.py`. You should tweak around these values with respect to your own provided training data.

4) Before Training

Before you start training, make sure your log is stored at the root of the `duckieTrainer` folder. It should be named as `train.log`.

Make sure you have saved all the desired trained models into `duckieModels`. Trust me you do not want your overnight training overwritten by accident. Yes I have been through losing my overnight training result.

5) Train it

To train your model:

```bash
$ python3 train.py
```

To observe using tensorboard, run this command in the `duckieTrainer` directory:

```bash
$ tensorboard --logdir logs
```

You should be able to also see your training status at `http://localhost:6006/`. If your computer is accessible by other computers, you can also see it by visiting `http://TRAINERIP:6006`

6) Things to improve

There are a lot of things could be improved as this is an overnight hack for me. The data loading could be maybe more efficient. Currently it just load all and stores all in a global variable. The training loss reference might not be the best. The optimizer might be improved. And most importantly, the way of choosing which model to use could be drastically improved.

7) Troubleshooting

Resolution: Currently there is no known fix other than cross your fingers and run again and reducing your batch size.

4.6. The duckieModels

This is a folder created just for you to keep track of all your potential models. There is nothing functional in it.

4.7. The duckieChallenger

This is the folder where you submit to challenge. The folder is structured as follows:

```
├── Dockerfile                      # Docker file used for compiling a
  container.                     # Modify this file if you added file,
│                             etc.
├── helperFncs.py               # Helper file for all helper func-
     tions.
├── requirements.txt           # All required pip3 install.
├── solution.py                # Your actual solution
└── submission.yaml        # Submission configuration.
```

After you put your trained model FrankNet.h5 in this folder, you can proceed as normal submission:

```
$ dts challenges submit
```

Or run locally:

```
$ dts challenges evaluate
```

An example submission looks like this

4.8. Acknowledgement

We would like to thank: Anthony Courchesne and Kay (Kaiyi) Chen for their help and support during the development of this baseline.
This section describes the basic procedure for making a submission with a model trained in simulation using residual policy learning with PyTorch and ROS. In this approach, we use the basic Duckietown lane following stack as the base policy, and we use reinforcement learning to improve it.

**KNOWLEDGE AND ACTIVITY GRAPH**

<table>
<thead>
<tr>
<th>Requires:</th>
<th>That you have made a submission with the ROS template.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Results:</td>
<td>You have a submission that leverages both our ROS stack and reinforcement learning.</td>
</tr>
</tbody>
</table>

Before getting started, you should be aware that this baseline is a combination of the RL baseline and of the ROS template. It is recommended that you are familiar for each of those templates and baselines, as the workflow of this one is similar to those. Here are some links:

- RL baseline
- ROS template
- Classical Duckietown baseline

You should also make sure you have access to good hardware. A recent graphics card (probably GTX1060+) is a must, and more than 8GB of RAM is required.

### 5.1. Quickstart

To train a policy, you should first make sure that Docker on your machine can access the GPU/CUDA. You should also install CUDA10.2+ locally.

Here's a few pointers:

- nvidia-docker
- CUDA 11

Clone this repo:

```
$ git clone https://github.com/duckietown/challenge-aido_LF-baseline-RPL-ros.git
```

Change into the directory:

```
$ cd challenge-aido_LF-baseline-RPL-ros
```

Test the submission, either locally with:
or make an official submission when you are ready with

```
$ dts challenges submit --challenge CHALLENGE_NAME
```

You can find the list of challenges here. Make sure that it is marked as “Open”.

### 5.2. Baseline Overview

Since, this baseline uses both ROS and ML, we need to train inside an environment where both ROS and PyTorch are installed. We will use Docker for this purpose.

The ROS template already provides us with a submission docker image. Our strategy here is to directly use that agent docker image during training, but we’ll the addition of the simulator and the training architecture on top.

This could have been done using a second running docker container to provide a network interface to the simulator, but this adds unnecessary overhead since we don’t actually need the added security that comes with running things separately.

So, every time we train, we build the agent docker image, and then the “trainer docker” image builds directly from the agent image, adding the simulator on top.

The final docker container then runs the simulator and the agent in parallel, allowing the agent to directly interface with the simulator, just like we do in the other machine learning baselines.
5.3. How to train your policy

From the `challenge-aido_LF-baseline-RPL-ros` directory, change into the `local_dev` directory:

```
$ cd local_dev
```

and open the `args.py` file. This is how you will control the training and testing in this repo. For now, just change the `--test` argument to `default=False`. Then, we can train with:

```
$ make run
```
As mentioned Section 5.2 - Baseline Overview, this will first build two subsequent docker images. This might take a while. Then, it will train an RL policy over the ROS stack inside Docker.

When it finishes, see how it works. Simply change the `--test` flag back to `default=True` in `args.py` and test with:

```
$ make run
```

This will launch a simulator window on your host machine for you to view how your agent performs. You should see something like this:

![Figure 5.2](image)

You can use this gif to gauge how long it takes for the testing docker to start (do note that this assumes that the two required docker images have already been built!)

### 5.4. How to submit the trained policy

Make sure that `rosagent.py` uses the right weights for your RL agent. This is controlled by the `MODEL_NAME` global variable. Then follow the procedure in Section 5.1 - Quickstart to evaluate and submit.

### 5.5. How to improve your policy

First, you should probably improve the base ROS policy. By default, this baseline uses the basic `lane_following` demo that is provided in Duckietown.

You could build a Pure Pursuit controller, change the lane filter, etc. See the classical Duckietown baseline for more ideas. To do this, you would add your new ROS packages inside of `submission_ws`.

You could also limit RL’s influence over the final policy. Perhaps the current approach of giving it full control in [-1,1] action values isn’t restrictive enough. Perhaps it could be better if it could only change the base policy by smaller action values.

Or perhaps it’s the opposite: maybe the base policy needs to be changed by more than 1: since the min/max value that the base policy can output is 1/ -1, the RL policy would need to be able to output from -2 to 2 to fully correct it.

Here are some ideas for improving your policy:

- Check out the `dtRewardWrapper` in `rl_agent` and modify the rewards (set them higher or lower and see what happens). By default, this wrapper is not used: you will have to add it to `train.py`.
- Try resizing the images. Make them smaller to have faster training, or bigger for making sure that RL can extract everything it can from them. You will need to also edit the layers in `ddpg.py` accordingly.
- Try making the observation image grayscale instead of color.
- Try stacking multiple images, like 4 monochrome images instead of 1 color image. You will need to also edit the layers in `ddpg.py` accordingly.
• You can also try increasing the contrast in the input to make the difference between road and road-signs clearer. You can do so by adding another observation wrapper.
• Cut off the horizon from the image (and correspondingly change the convnet parameters).
• Check out the default hyperparameters in `local_dev/args.py` and tune them. For example increase the `expl_noise` or increase the `start_timesteps` to get better exploration.
• (more sophisticated) Use a different map in the simulator, or - even better - use randomized maps. But be mindful that some maps include obstacles on the road, which might be counter-productive to a LF submission.
• (more advanced) Use a different/bigger convnet for your actor/critic. And add better initialization.
• (very advanced) Use the ground truth from the simulator to construct a better reward
• (extremely advanced) Use an entirely different training algorithm - like PPO, A2C, or DQN. Go nuts. But this might take significant time, even if you’re familiar with the matter.

5.6. Sim2Real Transfer (Optional)

You should try your agent on the real Duckiebot.

It is possible, even likely, that your agent will not generalize well to the real environment. One approach to mitigate this problem is to randomize the simulator environment during training, in the hope that this improves generalization. This approach is referred to as “Domain Randomization”.

To implement this, you will need to modify the `local_dev/env.py` file. You’ll notice that we launch the `Simulator` class from `gym-duckietown`. When we take a look at the constructor, you’ll notice that we aren’t using all of the parameters listed. In particular, the three you should focus on are:

• `map_name`: What map to use; hint, take a look at `gym_duckietown/maps` for more choices
• `domain_rand`: Applies domain randomization, a popular, black-box, sim2real technique
• `randomized_maps_on_reset`: Slows training time, but increases training variety.

Mixing and matching different values for these will help you improve your training diversity, and thereby improving your evaluation robustness!
PART F

Reference manual

We have built some tools and infrastructure to make it easy to build solutions. These tools may be helpful in building an efficient workflow for developing and testing your solutions before you submit them.

Contents

- Unit F-1 - dts challenges CLI .................................................................73
- Unit F-2 - Using the Evaluator .................................................................75
- Unit F-3 - Advanced submission options ..............................................76
This section is a reference for how to interact with the challenges server with the command line.

1.1. Account info
Use this command to see the status of your account:

```bash
$ dts challenges info
```

1.2. Local evaluation
The `evaluate` command allows you to do a local evaluation of your submission:

```bash
$ dts challenges evaluate
```

1.3. Submitting a submission
The `submit` command allows you to submit the solution in the current directory:

```bash
$ dts challenges submit
```

There are many options for this command, explained in Unit F-3 - Advanced submission options.

1.4. List submissions
The `list` command allows you to see all of your submissions:

```bash
$ dts challenges list
```

1.5. Reset a submission
`Resetting a submission` means that you discard the evaluations already performed and you force them to be done again.

```bash
$ dts challenges reset --submission ID
```

1.6. Retire a submission
Retiring a submission means that you declare the submission void. It will not be evaluated and previous results will be discarded.

```
$ dts challenges retire --submission ID
```

### 1.7. Follow the fate of a submission

The `follow` command polls the server to see whether there are updates:

```
$ dts challenges follow --submission ID
```

### 1.8. Defining a challenge

The `define` command allows to define a challenge:

```
$ dts challenges define
```
This section describes how to use the Challenges evaluators.

2.1. Evaluators
An evaluator is a machine that is in charge of evaluating the protocols.

2.2. Running your own evaluator
We have several evaluators online that process jobs.
If you want to avoid waiting in the queue for too long, you can run your own evaluator.
The command line is:

```
$ dts challenges evaluator --continuous
```

This evaluator will connect to the server and execute preferentially your submissions.

2.3. Advanced options for evaluator

1) Naming evaluator
Use the option `--name` to name the evaluator instance:

```
$ dts challenges evaluator --name a name
```

Otherwise the name is going to be autogenerated.
For example:

```
$ dts challenges evaluator --name Instance1 &
$ dts challenges evaluator --name Instance2 &
```

2) Run a specific submission
Run the evaluator on a specific submission:

```
$ dts challenges evaluator --submission ID
```

This evaluates a specific submission.
Note that to force re-evaluation of a submission, you must first reset the submission.
Also note that you cannot re-evaluate a submission that has been “retired”.
This section describes additional options for the `dts challenges submit` command.

### 3.1. submission.yaml file

Each submission directory has a file `submission.yaml` containing the following information:

```yaml
protocol: protocol  # do not change
challenge: challenge name(s)
user-label: optional label
user-payload: optional user payload
```

You can override these using the command line, as explained below.

### 3.2. Specifying the challenge

However you can also pass the name as a parameter `--challenge`:

```
$ dts challenges submit --challenge challenge name
```

The names of the challenges can be seen at this page.

For example, if you would only like to submit to LF validation system, you can do it as:

```
$ dts challenges submit --challenge aido3-LF-sim-validation
```

If you would like to submit to multiple specific challenges, you can do it in the yaml file:

```
protocol: aido2_db18_agent-z2  # do not change
challenge: [challenge1_name,challenge2name,...]
```

### 3.3. Metadata

You can attach two pieces of metadata to your submission.

1. A human-readable label for your identification.
2. A small JSON payload that describes the details of your submission, such as the parameters that you used for your algorithm.

To specify the label, use the option `--user-label`:
To specify the payload, use the option `--user-meta` and specify a JSON structure:

```
$ dts challenges submit --user-meta '{"param":"1"}'
```

### 3.4. Skip Docker cache

Use the option `--no-cache` to avoid using the Docker cache and re-build your containers from scratch:

```
$ dts challenges submit --no-cache
```