Data Sciense Project

Project structure:

1. Project Skeleton
    1. Content list
    2. Writers
    3. Goal
    4. Mathmatical representation of the problem
2. Data
    1. data explanation
    2. data sample
    3. Visualisation functions
3. Scoring of algorithms
    1. Air Quality Scores
    2. Regulation Valuation Score
    3. Final Score
4. Algorithms
    1. Simple Algorithms
        1. DAO - always open
        2. Axe - open if lower outdoor
        3. Mountains Cut - greedy algorithm
    2. Genetic Algorithms
    3. Reinforcement Deep Learning
5. Summarize
    1. The oracle tell
    2. Comparison of the methods we used
    3. Summary of our project work process and the lessons learned

Writers

Chai Leiman - id: 311227938

Rea Haas - id: 311600555

Goal of the Project - Reduce Cancer, Save Lives

Background

One of the major causes of mortality today is air pollution. According to the WHO, World Health Organization, an estimated 4.2 million premature deaths globally are linked to ambient air pollution. According to the WHO, people spend 86.9% of their time indoors, therefore much of the damage is caused inside buildings due to indoor air pollution.

A significant portion of the average persons day is spent inside business-type buildings, such as offices, shopping malls, etc. Our solution aims to reduce exposure to air pollutants within such structures.

How is it Done?

Such business-type buildings usually have a central fresh-air system that insert air from the outsider into the building. When the system detects that there is an increase in external air pollution, it closes the fresh air system and thus prevents the entry of polluted air from the outside.

What are our Challenges?

1. Minimize the level of indoor air pollution
2. Keeping an adequate level of oxygen indoors

If oxygen were not an issue, closing the fresh-air system indefinitely would prevent air-pollution from seeping in. However, it is not possible to close the fresh-air system indefinitely since occupants of a building are in need of oxygen. Therefore international standards, some of which are enshrined in law, determine the amount of air that must enter the building at any given time. By opening the fresh-

air system we indeed allow in oxygen, but at the same time air-pollution enters as well.

ASHRAE 62.1

We are following the ASHRAE 62.1 standard for ventilation and indoor air quality. The standard instructs, given certain parameters of a building such as size and number of occupants, the maximum time that the fresh-air system can be closed per given time-window.

The following animation demonstrates the implementation of the ASHRAE 62.1 standard. Every square represents a time slot, meaning a fixed length of time, such as 5 minutes each. At every time slot, meaning every 5 minutes, we need to decide whether to open (green) or close (red) the fresh-air system. Prior to making the decision, we need to take the standard into account. The ASHRAE 62.1 standard instructs that for every window of 4 time-slots, meaning, for every 20 minutes, a maximum of 2 time-slots can be closed. In other words, having the fresh-air system closed for over 10 minutes out of a 20 minute time-window is a violation of the standard. Moreover, it is important to understand that the window of 20 minutes is dynamic. At first, the window consists of time-slots 1 to 4. At the end of time-slot number 1, the window shifts one time-slot forwards to consist of time-slots 2 to 5, and so forth. These shifts are demonstrated in the animation bellow.

The Goal of the Project

As mentioned above, our general goal is to find the optimal balance at every given moment of the day between closing the fresh-air system to prevent air-pollution from entering the building and opening the system to allow entrance of fresh air. To do this we will use a database of air-pollution data from the Ministry of Environmental Protection. **Our goal is to be able to determine for any given day, the best vector of openings for that day while taking into account the ASHRAE 62.1 standard. Meaning, given a specific day, what will be the optimal sequence of opening and closing the fresh-air system while following the standard**

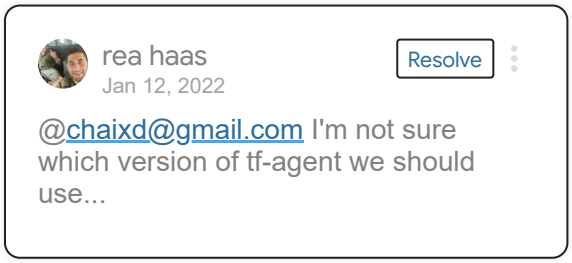
Mathmatical Representation of the Problem:

Given a graph of the Outdoor Air Quality (OAQ), find the optimal sequence of opening/closing the ventilation of a building, to optimize the Indoor Air Quality (IAQ).

Input:

1. An N dimention vector that is a time series of the OAQ measuremenets values (floats).
2. Time window size (number of time-slots)
3. Maximum value of permitted closing during a time window

Output: An N dimention boolean vector that is a the optimal open/close values for this time window (True=open, False=close).



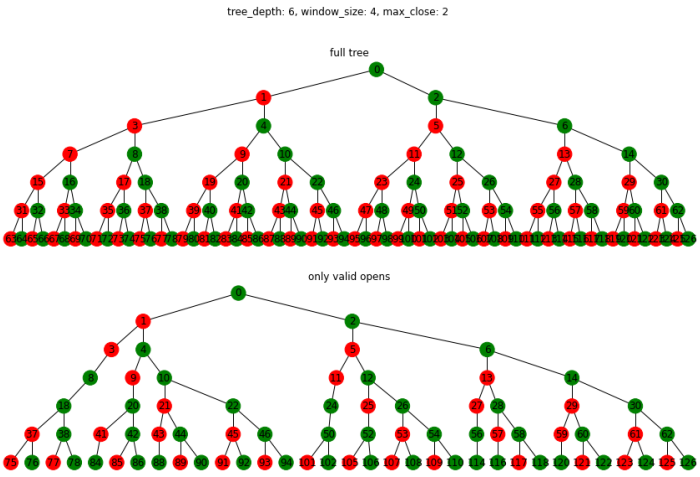
Good solution definition:

A good solution will be an algorithm that produces an open/close vector that is the optimal vector, or close to the optimal vector. We will build a measurement function to test our resultes.

Complexity of the Problem

The challenge described above is even more complex when taking into accound the fact that the current indoor air status is affected by previous decisions reagarding opening or closing the fresh-air system. An additional factor that adds to the complexity of our probelem, is the large solution space, meaning there is a wide range of possible solutions.

Bellow are desplayed two binary trees, describing the large solution space. The trees display six time slots, representing 5 minutes each. At every time slot, meaning every 5 minutes, we need to decide whether to open (green) or close (red) the fresh-air system. For example, decision sequence [open --> open --> close --> close --> open --> close --> close] brings us to node number 99, and that is only after 35 minutes. As we progress in time, the number of solutions grows exponentially. In the picture bellow, we see that the size of the situational space of the problem is exponent to the size of the problem. The first tree, "Full Tree", is a naive tree, desplaying the total number of options at every given time-slot. The second tree, "Only Valid Opens", desplays only the sequences that are possible given the limitations of the ASHRAE 62.1 stadard for ventilation. In the example bellow, the standard for ventilation limits us to maximum of 2 "close" for every 4 time-slots.



rea haas
Jan 12, 2022
Resolve

@chaixd@gmail.com
This cell make the notebook to run faster.

Imports

```
# %%capture
!pip install -U pandas==1.3.5  ## ?1.1.5
!pip install geneal==0.4.0
!pip install -U tensorflow==2.7.0
!pip install -U tf-agents==0.9.0  # 0.10.0  # ?0.11.0
!pip install -U matplotlib==3.1.3  # The latest version (3.5.0) not working
!pip install -U keras==2.7.0  # ==2.6.0
```

```
Collecting pandas==1.3.5
  Downloading pandas-1.3.5-cp37-cp37m-manylin
     |████████████████████████████████| 11.3
Requirement already satisfied: python-dateuti
Requirement already satisfied: pytz>=2017.3 i
Requirement already satisfied: numpy>=1.17.3
Requirement already satisfied: six>=1.5 in /u
Installing collected packages: pandas
  Attempting uninstall: pandas
    Found existing installation: pandas 1.1.5
    Uninstalling pandas-1.1.5:
      Successfully uninstalled pandas-1.1.5
ERROR: pip's dependency resolver does not cur
google-colab 1.0.0 requires pandas~=1.1.0; py
Successfully installed pandas-1.3.5
WARNING: The following packages were previous
  [pandas]
You must restart the runtime in order to use
```

RESTART RUNTIME

```
Collecting geneal==0.4.0
  Downloading geneal-0.4.0.tar.gz (22 kB)
Requirement already satisfied: numpy in /usr/
Requirement already satisfied: matplotlib in
Requirement already satisfied: scipy in /usr/
Requirement already satisfied: networkx in /u
Requirement already satisfied: pandas in /usr
Requirement already satisfied: pyparsing!=2.0
Requirement already satisfied: cycler>=0.10 i
Requirement already satisfied: kiwisolver>=1.
Requirement already satisfied: python-dateuti
Requirement already satisfied: six>=1.5 in /u
Requirement already satisfied: pytz>=2017.3 i
Building wheels for collected packages: genea
  Building wheel for geneal (setup.py) ... do
  Created wheel for geneal: filename=geneal-0
  Stored in directory: /root/.cache/pip/wheel
Successfully built geneal
Installing collected packages: geneal
Successfully installed geneal-0.4.0
Requirement already satisfied: tensorflow==2.
Requirement already satisfied: libclang>=9.0.
Requirement already satisfied: protobuf>=3.9.
Requirement already satisfied: typing-extensi
Requirement already satisfied: tensorflow-io-
Requirement already satisfied: keras-preproce
Requirement already satisfied: google-pasta>=
Requirement already satisfied: tensorflow-est
Requirement already satisfied: keras<2.8,>=2.
Requirement already satisfied: six>=1.12.0 in
Requirement already satisfied: grpcio<2.0,>=1
Requirement already satisfied: flatbuffers<3.
Requirement already satisfied: termcolor>=1.1
Requirement already satisfied: astunparse>=1.
Requirement already satisfied: gast<0.5.0,>=0
Requirement already satisfied: tensorboard~=2
Requirement already satisfied: absl-py>=0.4.0
Requirement already satisfied: h5py>=2.9.0 in
Requirement already satisfied: numpy>=1.14.5
Requirement already satisfied: wheel<1.0,>=0.
```

```
Requirement already satisfied: wrapt>=1.11.0
Requirement already satisfied: opt-einsum>=2.
Requirement already satisfied: cached-propert
Requirement already satisfied: requests<3,>=2
Requirement already satisfied: google-auth<3,
Requirement already satisfied: google-auth-oa
Requirement already satisfied: markdown>=2.6.
Requirement already satisfied: setuptools>=41
Requirement already satisfied: tensorboard-da
Requirement already satisfied: tensorboard-pl
Requirement already satisfied: werkzeug>=0.11
Requirement already satisfied: pyasn1-modules
Requirement already satisfied: rsa<5,>=3.1.4
Requirement already satisfied: cachetools<5.0
Requirement already satisfied: requests-oauth
Requirement already satisfied: importlib-meta
Requirement already satisfied: zipp>=0.5 in /
Requirement already satisfied: pyasn1<0.5.0,>
Requirement already satisfied: urllib3!=1.25.
Requirement already satisfied: chardet<4,>=3.
Requirement already satisfied: idna<3,>=2.5 i
Requirement already satisfied: certifi>=2017.
Requirement already satisfied: oauthlib>=3.0.
Collecting tf-agents==0.9.0
  Downloading tf_agents-0.9.0-py3-none-any.wh
     |████████████████████████████████| 1.3 M
Requirement already satisfied: wrapt>=1.11.1
Requirement already satisfied: cloudpickle>=1
Requirement already satisfied: gin-config>=0.
```

```
!pip freeze
```

```
tabulate==0.8.9
tblib==1.7.0
tensorboard==2.7.0
tensorboard-data-server==0.6.1
tensorboard-plugin-wit==1.8.1
tensorflow @ file:///tensorflow-2.7.0-cp37
tensorflow-datasets==4.0.1
tensorflow-estimator==2.7.0
tensorflow-gcs-config==2.7.0
tensorflow-hub==0.12.0
tensorflow-io-gcs-filesystem==0.23.1
tensorflow-metadata==1.5.0
tensorflow-probability==0.15.0
termcolor==1.1.0
terminado==0.12.1
testpath==0.5.0
text-unidecode==1.3
textblob==0.15.3
tf-agents==0.9.0
Theano-PyMC==1.1.2
thinc==7.4.0
threadpoolctl==3.0.0
tifffile==2021.11.2
toml==0.10.2
tomli==2.0.0
toolz==0.11.2
torch @ https://download.pytorch.org/whl/c
torchaudio @ https://download.pytorch.org/
```

```
torchsummary==1.5.1
torchtext==0.11.0
torchvision @ https://download.pytorch.org
tornado==5.1.1
tqdm==4.62.3
traitlets==5.1.1
tweepy==3.10.0
typeguard==2.7.1
typing-extensions==3.10.0.2
tzlocal==1.5.1
uritemplate==3.0.1
urllib3==1.24.3
vega-datasets==0.9.0
wasabi==0.9.0
wcwidth==0.2.5
webencodings==0.5.1
Werkzeug==1.0.1
widgetsnbextension==3.5.2
wordcloud==1.5.0
wrapt==1.13.3
xarray==0.18.2
xgboost==0.90
xkit==0.0.0
xlrd==1.1.0
xlwt==1.3.0
yellowbrick==1.3.post1
zict==2.0.0
zipp==3.7.0
```

```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import matplotlib.collections as collections

import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import backend as K

import tf_agents
from tf_agents import agents, environments, metrics
from tf_agents.trajectories import time_step
from tf_agents.replay_buffers import tf_uniform_replay_buffer
from tf_agents.policies import random_tf_policy

import seaborn as sns
from geneal.genetic_algorithms import BinaryGenAlgSolver
from functools import partial
from itertools import product
from typing import Any, Callable

# from tensorforce.environments import Environment
# from tensorforce.agents import Agent
# from tensorforce.execution import Runner
```

```
import datetime
```

```
gpu_devices = tf.config.experimental.list_physical_devices("GPU")
for device in gpu_devices:
    tf.config.experimental.set_memory_growth(device, True)
```

```
DTYPE = tf.float32
```

```
# This variable effect the runtime of the notebook.
# This variable is use to set the number of epochs for all the learning algoritems.
# For quick run, set to 1.
# For normal run, set to 5.
# for long run set to 10.
epochs_base_const = 1
quick_run = True
```

Data

```
example_day = np.array([38.4, 36.7, 36.6, 42.3, 46. , 36.2, 31.8, 32.6, 32.3, 32.2, 32.6,
       32.6, 33.1, 32.3, 33.2, 34.4, 35.6, 34.1, 30.8, 30.9, 32.4, 34.1,
       35.2, 33.5, 33.1, 32.3, 31.7, 32.6, 36. , 40.6, 40.9, 41.5, 44.2,
       39.7, 39.5, 41.1, 42. , 39.8, 41.1, 42.1, 40.8, 38.8, 42.1, 48.6,
       55.2, 57.8, 55.4, 50.1, 45. , 42. , 50.2, 63.3, 73. , 76.9, 78.8,
       74.9, 64.1, 59.8, 60.3, 53.7, 56.1, 54.2, 52. , 53.9, 58. , 60.9,
       55.6, 51.3, 49.3, 53.6, 57.4, 58. , 56.3, 52.4, 50.1, 50.8, 52.9,
       57.9, 57.5, 58.9, 56.6, 58. , 65.7, 72.9, 74.4, 70.4, 74. , 75.6,
       69.7, 61.2, 31.1, 28.4, 24.3, 25.3, 25.1, 21.4, 20.2, 22.6, 18.8,
       16.2, 17.6, 20.7, 21. , 20.6, 20.4, 22.3, 21.3, 18.4, 21.8, 19. ,
       17.1, 15.8, 13.6, 17.2, 14.7, 13.1, 15. , 13.5, 12.3, 11.4,  9. ,
        7.1, 10.8, 14.2, 12. ,  9. ,  8.3, 11.4, 10.9,  9.2,  7.4,  7.9,
        9.9,  7.4,  6.5,  8.3,  7.9,  6.2,  6.9,  8.3,  6. ,  7.1,  8.6,
        8.5,  7.4,  8.2,  9.4, 10.4,  9.3, 10.4,  9.4,  8.5,  6.5,  9.3,
       11.3, 10.8, 12.9, 10.8, 14.5, 16.8, 12. , 14.7, 12.8, 13.9, 11.3,
       11.5, 13.5, 16.3, 13.4, 15.8, 15. , 18.9, 19.3, 18.2, 26.2, 29.7,
       29.5, 26.7, 24.8, 28.8, 39.8, 41.6, 35.1, 38.3, 35.9, 39. , 43.1,
       41.2, 38. , 37.5, 35.6, 36.8, 38.7, 46.8, 62.9, 60.6, 51.6, 46.4,
       45.7, 45.8, 47.4, 53.5, 60. , 71.1, 77.1, 76.5, 75.3, 69.9, 68.9,
       61.6, 59.1, 62.8, 72.1, 73. , 69.9, 69.2, 66.3, 54.2, 46.2, 48.1,
       55.2, 54.5, 53.7, 50.4, 49.6, 49.7, 55.3, 61.5, 58.6])
```

```
example_day.shape
```

```
(229,)
```

import data

```
data = None
try:
  df = pd.read_pickle("/content/data for rea.pkl")
  data = tf.constant(df.values, dtype=DTYPE)
  X_train = data
except:
  X_train = tf.cast(tf.tile([example_day], (100,1)), dtype=DTYPE)

X_train
```

```
<tf.Tensor: shape=(100, 229), dtype=float32,
array([[38.4, 36.7, 36.6, ..., 55.3, 61.5, 58
       [38.4, 36.7, 36.6, ..., 55.3, 61.5, 58
       [38.4, 36.7, 36.6, ..., 55.3, 61.5, 58
       ...,
       [38.4, 36.7, 36.6, ..., 55.3, 61.5, 58
       [38.4, 36.7, 36.6, ..., 55.3, 61.5, 58
       [38.4, 36.7, 36.6, ..., 55.3, 61.5, 58
```

Scores

[ ] ↳ *36 cells hidden*

Visualization

To present the Algorithm's performance, we will create a graph that displays the outside air-pollution (in blue), the algorithm's decisions (openings in green, closings in red), and the resulted indoor air-pollution (in orange)

```
def fill_ax_for_ploting_decisions(ax: 'matplotlib.pyplot.axes', day:'np.ndarray[np.float]'
  x = range(day.size)

  ax.plot(x,day, color = 'blue')
  ax.plot(x,iaq, color = 'darkorange')
  ax.set_ylim(bottom = 0)
  ymin, ymax = ax.get_ylim()

  # coloring the background with green for open or red for closed.
  for i, value in enumerate(decisions):
    color = "green" if value else "red"
    ax.axvspan(i-0.5, i+0.5, facecolor=color, alpha=0.35)
```

```
def show(day:'np.ndarray[np.float]',iaq:'np.ndarray[np.float]', decisions:'np.ndarray[np.b
  assert day.shape == decisions.shape

  fig, ax = plt.subplots(figsize=(20,10))

  fill_ax_for_ploting_decisions(ax, day, iaq, decisions)

  fig.tight_layout()
```

Algorithms

```
algorithms_scores = {}
algorithms_decisions = {}
algorithms_runtime_duration ={}


print(algorithms_scores)
print(algorithms_decisions)
print(algorithms_runtime_duration)
```

```
{}
{}
{}
```

```
example_window = tf.constant(24)
example_max_close = tf.constant(7)


# global values: example_window.numpy(), example_max_close.numpy()

def run_and_save_algo(algo: callable, day_to_use):
    start_time = datetime.datetime.now()
    decisions = algo(day_to_use, example_window.numpy(), example_max_close.numpy())
    end_time = datetime.datetime.now()
    runtime_duration = (end_time - start_time).microseconds

    score, indoor_air = iaqScore(day_to_use, decisions)

    algorithms_decisions[algo.__name__] = decisions
    algorithms_scores[algo.__name__] = maximize_score(day_to_use, algorithms_decisions[alg
    algorithms_runtime_duration[algo.__name__] = runtime_duration

    return score, indoor_air, decisions
```

Benchmark Algorithms

We will present a few basic analitical algorithms as a benchmark.

Daily Always Open

The most naive algorithm that meets the conditions, and the one that is in practice implemented in all of the buildings, is of course the one that opens all the time.

```
def dao(day:'np.ndarray[np.float]', window:int = None, max_close:int = None) -> 'np.ndarra
  return np.ones(example_day.shape, dtype=bool)


day_to_use = example_day

score, indoor_air, decisions = run_and_save_algo(dao, day_to_use)


show(day_to_use, indoor_air, decisions)
display(f"DAO algorithm got score of {score} and is {'' if is_valid_closed(decisions, exam
```

```
'DAO algorithm got score of 0.99365412445079
09 and is folowing the standard'
```

```
print(algorithms_runtime_duration)
```

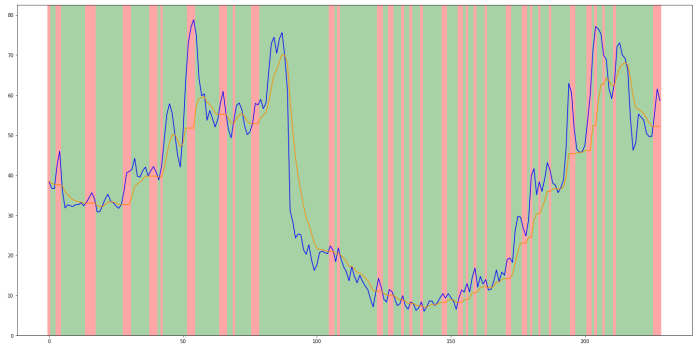
```
{'dao': 1327}
```

AXE - open if lower outdoors

The next naive algorithm the also prevents air-pollution from entering the building, simply closes when the indoor air-pollution is higher than the outdoor air-pollution, while taking into account the ventilation standard

```
def axe_decision(oaq_value: float,
                 iaq_value: float,
                 window_open: 'np.ndarray[np.bool]',
                 window: int,
                 max_close: int):
    # add one "close" slot to the end of the window:
    OPEN = True
    window_open.append(not OPEN)
    if not is_valid_closed(window_open, window=window, maxClose=max_close):
      return OPEN
    else:
      return oaq_value < iaq_value

def axe(day:'np.ndarray[np.float]', window:int, max_close:int) -> 'np.ndarray[np.bool]':
  decisions = []
  iaq_value = day[0]

  for oaq_value in day:
    decision = axe_decision(oaq_value, iaq_value, decisions[-window:], window, max_close)
    decisions.append(decision)
    if decisions[-1]:
      iaq_value = iaqc(oaq_value, iaq_value)

  return np.array(decisions)


day_to_use = example_day

score, indoor_air, decisions = run_and_save_algo(axe, day_to_use)

show(day_to_use, indoor_air, decisions)
display(f"AXE algorithm got score of {score} and is {'' if is_valid_closed(decisions, exam
```

```
'AXE algorithm got score of 0.95805791899804
74 and is folowing the standard'
```



Mountains cut

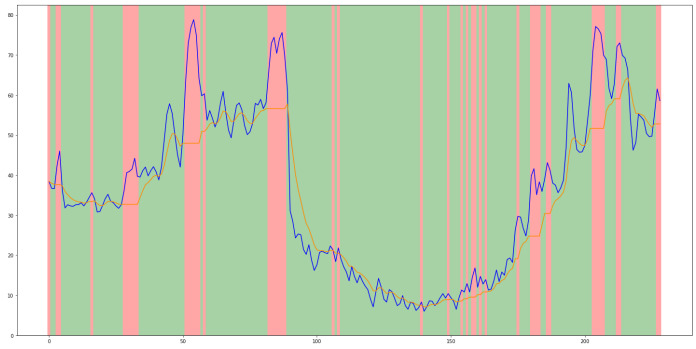
We created an additional algorithm that is heuristicly based.

The aim of the following algorithm is to find the "most advantageous closing point" at each given time, and decide what to do then. If it is possible to close at that time according to the ventilation standard, then it will close, and if not, then it will leave it open and continue on to the next "most advantageous closing point"

```
NOT_DEFIEND = -1
OPEN = True
```

```
CLOSED = not OPEN

def not_defined_to_open(trinary_array) -> 'np.ndarray[np.bool]':
    opens_decisions =  np.array(trinary_array) != CLOSED
    return opens_decisions


def mountains_cut(day:'np.ndarray[np.float]', window:int, max_close:int) -> 'np.ndarray[np
    closed_points = np.full(day.shape, NOT_DEFIEND)
    max_indexs = np.flip(np.argsort(day))

    for max_index in max_indexs:
        closed_points[max_index] = CLOSED

        temp_decisions = not_defined_to_open(closed_points)
        if is_valid_closed(temp_decisions, window=window, maxClose=max_close):
            continue  # the colsed was valid...
        else:
            closed_points[max_index] = OPEN

    score, indoor_air = iaqScore(day, closed_points)

    for i, d in enumerate(closed_points):
        if day[i] < indoor_air[i]:
            closed_points[i] = OPEN
    # print("optimize: \n{c}".format(c=closed_points))

    return closed_points


day_to_use = example_day

score, indoor_air, decisions = run_and_save_algo(mountains_cut, day_to_use)

show(day_to_use, indoor_air, decisions)
display(f"mountains_cut algorithm got score of {score} and is {'' if is_valid_closed(decis
```

```
'mountains_cut algorithm got score of 0.9233
44898173993 and is folowing the standard'
```



Genetic algorithem

The following genetic algorithm draws inspiration from life and the Theory of Evolution. The purpose is to create a greedy heuristic algorithm for finding the optimum of a problem. We do this by creating a set of possible solutions, we give each solution a score, and then pair the better solutions and "kill" the inferior solutions. In addition, we have methods for adding "mutations". The purpose of the mutations is to increase the variety of solutions and to give the inferior solutions a chance to pair up and form a consequent generation. This prevents the algorithm from getting stuck in a local minimum.

Our solution achieves a good result but it takes quite a long time (even though it technicaly runs in a linear complexity).

```
def genetic_solution(day:'np.ndarray[np.float]', window:int, maxClose:int) -> 'np.ndarray[
  fitness_func = lambda opens: maximize_score(day, opens, window, maxClose)
  solver = BinaryGenAlgSolver(
    n_genes=len(day),
    fitness_function=fitness_func,
    n_bits=1, # number of bits describing each gene (variable)
    pop_size=700, # population size (number of individuals)
    max_gen=epochs_base_const*100, # maximum number of generations
    mutation_rate=0.0075, # mutation rate to apply to the population
    selection_rate=0.33, # percentage of the population to select for mating
```

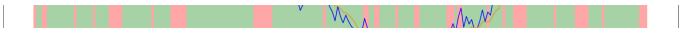
```
        selection_strategy="roulette_wheel", # strategy to use for selection.
        verbose = not False,
        show_stats = False,
        plot_results = False,
      )
      solver.solve()
      return solver.best_individual_

  day_to_use = example_day

  score, indoor_air, decisions = run_and_save_algo(genetic_solution, day_to_use)

  show(day_to_use, indoor_air, decisions)
  display(f"genetic algorithm got score of {score} and is {'' if is_valid_closed(decisions,
```

```
Iteration: 10
Best fitness: -0.9574458532075533
Iteration: 20
Best fitness: -0.9418277607706513
Iteration: 30
Best fitness: -0.9320808826176555
Iteration: 40
Best fitness: -0.9282551335525905
Iteration: 50
Best fitness: -0.9252256139593589
Iteration: 60
Best fitness: -0.9231672525818296
Iteration: 70
Best fitness: -0.9228235113999
Iteration: 80
Best fitness: -0.9219094565037723
```

Deep learning

```
Best fitness: -0.9217350460518744
```

In retrospect we understood that the problem is harder than we had originally thought. Therefore we will try using various approaches to do an overfit for one day, as a sanity test. The reasoning being that if an easy overfit fails, then training extensive data will likely fail as well.



In this approach, instead of using a classic loss function, we use the score given by the openings as the loss function.

How is this done? A loss function is basically a function that receives two arguments: the output of the network and an additional argument. In classic supervised learning, this argument is the desired output of the network, but this is not obligatory. We used the argument to give the loss function the daily pollution, which is used along with the network output in order to calculate the daily score.

```
K.clear_session()
np.random.seed(42)
tf.random.set_seed(42)

day_length = X_train.shape[1]
display(day_length)
```

```
229
```

```
@tf.function
def minimize_loss(days, preds):
  return batch_minimize_score(days, preds, window_size = example_window, maxClose = exampl


@tf.function
def probabilities_to_boolean(probabilities_array, training = None): #get_action
    input_shape = tf.shape(probabilities_array)
    #bit random in training and deterministic when not
    threshhold = tf.random.uniform(shape = input_shape) if training else tf.constant(.5, d
    return probabilities_array > threshhold
```

Naive approch

We will try to directly use the score function as the loss function

```
classic_model = keras.models.Sequential([
    keras.layers.LayerNormalization(input_dim=day_length),
    keras.layers.Dense(512, activation="relu"),
    keras.layers.Reshape((-1,1)),
    keras.layers.Conv1D(filters=32, kernel_size=(example_window.numpy(),)),
    keras.layers.Flatten(),
    keras.layers.Dense(512, activation="relu"),
    keras.layers.Dense(512, activation="relu"),
    keras.layers.Dense(day_length, activation="sigmoid"),
    keras.layers.Lambda(probabilities_to_boolean)
], name = 'naive_model')

classic_model.summary()
```

```
Model: "naive_model"
_________________________________________________
 Layer (type)                Output Shape
=================================================
 layer_normalization (LayerN  (None, 229)
 ormalization)

 dense (Dense)               (None, 512)

 reshape (Reshape)           (None, 512, 1)

 conv1d (Conv1D)             (None, 489, 32)

 flatten (Flatten)           (None, 15648)

 dense_1 (Dense)             (None, 512)

 dense_2 (Dense)             (None, 512)

 dense_3 (Dense)             (None, 229)

 lambda (Lambda)             (None, 229)
```

```
=================================================
Total params: 8,511,439
Trainable params: 8,511,439
Non-trainable params: 0
_________________________________________________
```

The loss function receives the network results and a pre-defined inputs (usually the desired values), and issues some sort of score based on that. In this case we gave the loss function the days as pre-defined values and together with the openings that the network outputs, the loss function calculates the daily score

```
classic_model.compile(loss=minimize_loss, optimizer="adam")
try:
  classic_model.fit(X_train, X_train, batch_size = 64, epochs = epochs_base_const*5, valid
except ValueError as e:
  print(e.args[0].rpartition('\n\n    ')[-1])
```

```
Epoch 1/5
ValueError: No gradients provided for any var
```

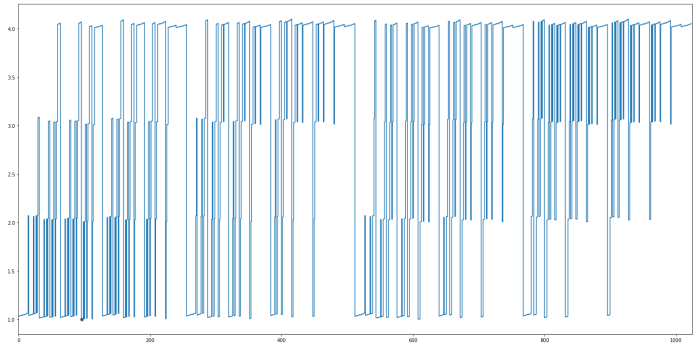
This approach failed since the loss function is either non-derivative or has a derivative of zero regarding the commands. That is, the loss function acts as a "stair function" of some sort.

To make things simple, we will demonstrate this on a day of 10 samples (meaning, there will be a space of 1024 sets of possible decisions - 2^10). We will calculate the score for each set of decisions and will receive the following graph (the minimum is highlighted in red)

```
n=10
preds = tf.constant(list(product([True,False],repeat=n)))
days = tf.cast(tf.tile([example_day[:n]], (len(preds),1)), dtype=DTYPE)
scores = batch_minimize_score(days, preds, tf.constant(n-2), maxClose = tf.constant(n//3))
```

```
fig, ax = plt.subplots(figsize=(20,10))
ax.plot(scores,drawstyle='steps-mid', marker ='o',markerfacecolor='red',markevery=[tf.argm
```

```
ax.set_xlim([0,2**n])
fig.tight_layout()
```



As mentioned before, the method of directly using the score function as a loss function did not work. Therefore, in order to create a loss function that is derivative, we will train networks that will mimic the loss function and use them as a loss function.

Training loss network

The score calculation is composed of two parameters: First, the number of times we violated the regulation by closing the ventilation. Second, the amount of pollution we prevented. Since direct training did not work, we will try a slightly different

training approach. We built two networks, each mimicking a function, and then combined them together as layers in an integrated funcional model.

Data generator for "Loss network"

The generator creates fabricated days that consist of randomly made-up levels of pollution and random openings and closings. It should be noted that the generator is not true to any existing data and therefore less sequential. For training purposes, we will transfer this data into a model that is aimed to mimic the loss function.

```
# general datagenerator

# call as:
# 1. network tm_violations_helper:  tm_dg = DataGenerator(tm_violations_helper, window_siz
# 2. network batch_iaq_score:       iaq_dg = DataGenerator(batch_iaq_score)


class DataGenerator(keras.utils.Sequence):
    """
    Generates data for keras loss networks.
    :return: A generator object that implement the "next()" function.
    """
    def __init__(self, batch_scoring, batch_size=32, shuffle=True, **batch_scoring_kargs):
        'Initialization'
        self.batch_size = batch_size

        # scoring params
        self.batch_scoring = batch_scoring
        self.max_val = 100
        self.day_length = len(example_day)
        self.batch_scoring_kargs = batch_scoring_kargs
        self.on_epoch_end()

    def __len__(self):
        'Denotes the number of batches per epoch'
        return 100

    def __getitem__(self, index):
        'Generate one batch of data'
        # Generate data
        X, y = self.__data_generation()

        return X, y

    def on_epoch_end(self):
        'Updates indexes after each epoch'
```

```
            pass

        def __data_generation(self):
            'Generates data containing batch_size samples'
            # Initialization
            days = tf.random.uniform(shape = (self.batch_size, self.day_length), maxval=self.m
            decisions = tf.round(tf.random.uniform(shape = (self.batch_size, self.day_length))

            Y = self.batch_scoring(days, tf.cast(decisions,tf.bool), **self.batch_scoring_karg
            X = tf.stack([days, decisions], axis =1) #return shape (batch_size, 2, day_length)
            return X, Y



def tm_violations_helper(day, opens,  *args, **kargs):
  return batchTmViolations(opens, *args, **kargs)

# Generator
tm_generator = DataGenerator(tm_violations_helper, window_size=example_window, maxClose=ex
```

TM net

We will define a network that is aimed to mimic the function that calculates the number of ventilation regulation violations. Since the network receives a binary vector (zeros and ones) as input, then there is a problem that the zeros "turn-off" the neurons. Therefore we first put a normalization layer that initializes the connection with "ones", so that the zeros are transferred to the network as a value other than zero.

```
# Design model
# Architecture
model_violations = keras.models.Sequential([
    keras.layers.InputLayer(input_shape=(2, day_length)), # recived [day, decisions]
    keras.layers.Lambda(lambda x: x[:, 1]),  # remove the part of the "day" recived by the
    keras.layers.LayerNormalization(beta_initializer = 'ones'),
    # keras.layers.Reshape((-1,1)),
    # keras.layers.Conv1D(filters=4, kernel_size=(example_window.numpy(),)), # filters=32
    # keras.layers.Flatten(),
    keras.layers.Dense(day_length - (example_window-1), activation="relu"),
    # keras.layers.Dense(512, activation="relu"),
    keras.layers.Dense(1),
],name = "tm_score_model")
```

```
model_violations.summary()
```

```
Model: "tm_score_model"
_________________________________________________
 Layer (type)                Output Shape
=================================================
 lambda_1 (Lambda)           (None, 229)

 layer_normalization_1 (Laye  (None, 229)
 rNormalization)

 dense_4 (Dense)             (None, 206)

 dense_5 (Dense)             (None, 1)

=================================================
Total params: 48,045
Trainable params: 48,045
Non-trainable params: 0
_________________________________________________
```

```
optimizer = keras.optimizers.Adam(learning_rate=1e-4)
model_violations.compile(loss='mse', optimizer=optimizer, metrics=["mae"])
```

The next cell allow us to train a network with changeing the learning rate of the learning process. This action is helpfull to quickly train the network at the beggining, and allow more precise learning as the learing process is going on.

```
def train_model_with_learning_rate_range(model, min_learning_rate: int, max_learning_rate:
    for i in range(min_learning_rate, max_learning_rate):
        print(f"i={i}, learning_rate: {10 ** -i}")
        # model_violations.optimizer = keras.optimizers.Adam(learning_rate=10 ** -i)
        K.set_value(model.optimizer.learning_rate, 10 ** -i)
        model.fit(tm_generator, epochs=epochs_base_const*2, validation_data=tm_generator)
```

```
train_model_with_learning_rate_range(model_violations, 3 , 6)
    # model_violations.fit(tm_generator, epochs=1000, validation_data=tm_generator)

# After ~25 apoches the network loss value stabalize with those values:
# Epoch 500/500

# 100/100 [==============================] - 3s 35ms/step - loss: 41.8520 - mae: 4.4132 -
# 100/100 [==============================] - 10s 100ms/step - loss: 78.0285 - mae: 6.6489
```

```
i=3, learning_rate: 0.001
Epoch 1/2
100/100 [==============================] - 2s
Epoch 2/2
100/100 [==============================] - 1s
```

```
i=4, learning_rate: 0.0001
Epoch 1/2
100/100 [==============================] - 1s
Epoch 2/2
100/100 [==============================] - 1s
i=5, learning_rate: 1e-05
Epoch 1/2
100/100 [==============================] - 1s
Epoch 2/2
100/100 [==============================] - 1s
```

```
# Save the model. This is commented out to allow full run of the notebook.
# tf.keras.models.save_model(model_violations, "model_violations_only_dense_layer_2200_epo
```

TM net trainnig

Training network: only 1 Dense layer with (day_length - (example_window-1)) neorons, and a second Dense layer to sum it. no convulotion layer.

Epoch 199/200 100/100 [==============================] - 1s 14ms/step - loss: 57.0698 - mae: 5.4967 - val_loss: 61.0760 - val_mae: 5.3381

Epoch 200/200 100/100 [==============================] - 1s 13ms/step - loss: 54.4774 - mae: 5.4024 - val_loss: 57.9389 - val_mae: 5.2452 <tensorflow.python.keras.callbacks.History at 0x7f4918af8850>

train 200 more apoches: (total of 400)

Epoch 199/200 100/100 [==============================] - 1s 13ms/step - loss: 46.5804 - mae: 4.9022 - val_loss: 49.9185 - val_mae: 4.9435

Epoch 200/200 100/100 [==============================] - 1s 13ms/step - loss: 46.3859 - mae: 4.8300 - val_loss: 49.5456 - val_mae: 5.2111

<tensorflow.python.keras.callbacks.History at 0x7f4918fee390>

train 600 more apoches: (total of 1000)

Epoch 599/600 100/100 [==============================] - 2s 16ms/step - loss: 44.2327 - mae: 4.5011 - val_loss: 43.8462 - val_mae: 4.6221

Epoch 600/600 100/100 [==============================] - 2s 16ms/step - loss: 43.5605 - mae: 4.5297 - val_loss: 44.2052 - val_mae: 4.4679 <tensorflow.python.keras.callbacks.History at 0x7f4918e83490>

train 600 more apoches: (total of 1600)

Epoch 599/600 100/100 [==============================] - 1s 15ms/step - loss: 30.2108 - mae: 3.7182 - val_loss: 29.3280 - val_mae: 3.7389 Epoch 600/600 100/100 [==============================] - 2s 16ms/step - loss: 29.8563 - mae: 3.7247 - val_loss: 28.8577 - val_mae: 3.5995 <tensorflow.python.keras.callbacks.History at 0x7f4918e04a90>

train 600 more apoches: (total of 2200)

100/100 [==============================] - 2s 16ms/step - loss: 16.4375 - mae: 2.9318 - val_loss: 15.8881 - val_mae: 2.9590 Epoch 600/600

100/100 [==============================] - 2s 16ms/step - loss: 15.5105 - mae: 2.9128 - val_loss: 15.9718 - val_mae: 2.8704 <tensorflow.python.keras.callbacks.History at 0x7f4918e83390>

Training: 4 filter in the convulotion layer.

Epoch 99/100 100/100 [==============================] - 4s 35ms/step - loss: 62.2390 - mae: 5.8461 - val_loss: 59.2680 - val_mae: 5.6213

```
Epoch 100/100 100/100
[==============================] - 4s
35ms/step - loss: 62.8819 - mae: 5.9137 - val_loss:
61.7635 - val_mae: 5.4766
<tensorflow.python.keras.callbacks.History at
0x7f4918799390>
```

train 200 more apoches: (total of 300)

```
Epoch 199/200 100/100
[==============================] - 4s
36ms/step - loss: 44.9927 - mae: 4.8197 - val_loss:
46.8314 - val_mae: 4.7050

Epoch 200/200 100/100
[==============================] - 4s
36ms/step - loss: 47.8316 - mae: 4.9384 - val_loss:
52.1949 - val_mae: 4.8155
<tensorflow.python.keras.callbacks.History at
0x7f4919112090>
```

train 200 more apoches: (total of 500)

```
Epoch 199/200 100/100
[==============================] - 4s
37ms/step - loss: 42.1251 - mae: 4.5120 - val_loss:
41.6142 - val_mae: 4.3005

Epoch 200/200 100/100
[==============================] - 4s
35ms/step - loss: 42.6882 - mae: 4.4851 - val_loss:
41.8070 - val_mae: 4.3309
<tensorflow.python.keras.callbacks.History at
0x7f4918365a50>
```

Training: only 1 filter in the convulotion layer.

```
Epoch 99/100 100/100
[==============================] - 3s
27ms/step - loss: 57.9428 - mae: 5.5985 - val_loss:
57.9487 - val_mae: 5.6419

Epoch 100/100 100/100
[==============================] - 3s
```

27ms/step - loss: 59.4634 - mae: 5.6960 - val_loss: 55.4362 - val_mae: 5.6257
<tensorflow.python.keras.callbacks.History at 0x7f490fa75610>

Train with 229 filters in the convolution layer.

Epoch 1/100 100/100 [==============================] - 62s 618ms/step - loss: 1556.7528 - mae: 21.7123 - val_loss: 89.5971 - val_mae: 7.4003

Epoch 2/100 100/100 [==============================] - 62s 617ms/step - loss: 90.1419 - mae: 7.2280 - val_loss: 81.0774 - val_mae: 7.0908

Epoch 3/100 100/100 [==============================] - 62s 616ms/step - loss: 83.8718 - mae: 6.9920 - val_loss: 79.1181 - val_mae: 6.6291

Epoch 4/100 100/100 [==============================] - 62s 617ms/step - loss: 79.8979 - mae: 6.8313 - val_loss: 78.9902 - val_mae: 7.0794

Epoch 5/100 100/100 [==============================] - 62s 616ms/step - loss: 81.0100 - mae: 6.9017 - val_loss: 107.7526 - val_mae: 6.6161

Epoch 6/100 100/100 [==============================] - 62s 617ms/step - loss: 76.8204 - mae: 6.6775 - val_loss: 80.5437 - val_mae: 6.5771

Epoch 7/100 100/100 [==============================] - 62s 616ms/step - loss: 80.2520 - mae: 6.7645 - val_loss: 78.7381 - val_mae: 6.1367

Epoch 8/100 100/100 [==============================] - 62s 616ms/step - loss: 89.1232 - mae: 7.1479 - val_loss: 73.6196 - val_mae: 6.6503

Epoch 9/100 100/100
[==============================] - 61s
615ms/step - loss: 78.2839 - mae: 6.7109 - val_loss:
73.4172 - val_mae: 6.7398

Epoch 10/100 100/100
[==============================] - 62s
618ms/step - loss: 85.2402 - mae: 6.9922 - val_loss:
76.3829 - val_mae: 7.0322

Epoch 11/100 100/100
[==============================] - 63s
635ms/step - loss: 87.5664 - mae: 7.1137 - val_loss:
77.3624 - val_mae: 7.0253

Epoch 12/100 100/100
[==============================] - 64s
636ms/step - loss: 85.7426 - mae: 6.9934 - val_loss:
76.1271 - val_mae: 6.9607

It's take too much time and not improving.

IAQC net

We will define a network that is aimed to mimic the function that calculates the score for the minimizing of pollution in the building, by changing openings and closings of the ventilation system.

Since this network experiences a similar problem of binary input, we solved the problem with a similar normalization layer.

```
# Generators
iaq_generator = DataGenerator(batch_iaq_score)
# Design model
# Architecture
model_iaq = keras.models.Sequential([
    keras.layers.LayerNormalization(beta_initializer = 'ones',input_shape=(2, day_length))
    keras.layers.Dense(day_length*2, activation="relu"),
    keras.layers.Dense(day_length*2, activation="relu"),
    keras.layers.Dense(day_length*2, activation="relu"),
    keras.layers.Flatten(),
    keras.layers.Dense(1),
], name = "iaq_score_model")
model_iaq.compile(loss='mse', optimizer="adam", metrics=["mae"])
```

```
model_iaq.summary()
```

```
Model: "iaq_score_model"
_________________________________________________________________
 Layer (type)                Output Shape              
=================================================================
 layer_normalization_2 (Laye  (None, 2, 229)
 rNormalization)

 dense_6 (Dense)             (None, 2, 458)

 dense_7 (Dense)             (None, 2, 458)

 dense_8 (Dense)             (None, 2, 458)

 flatten_1 (Flatten)         (None, 916)

 dense_9 (Dense)             (None, 1)

=================================================================
Total params: 527,159
Trainable params: 527,159
Non-trainable params: 0
_________________________________________________________________
```

```
model_iaq.fit(iaq_generator, epochs=epochs_base_const*1, validation_data=iaq_generator)
# After ~10 apoches the network loss value stabalize with those values:
# 100/100 [==============================] - 3s 26ms/step - loss: 0.0021 - mae: 0.0369 - v
```

```
100/100 [==============================] - 26
<keras.callbacks.History at 0x7f1d01a029d0>
```

combined

We will define a network that will give the final score by combining the two networks that mimic the partial-score functions

```
commonInput = keras.layers.Input(shape=(2, day_length))

out1 = model_iaq(commonInput)
out2 = model_violations(commonInput)

merged = keras.layers.Add()([out1,out2])
model_scoring = keras.Model(inputs=[commonInput], outputs=merged)
model_scoring.summary()
```

```
Model: "model"
_________________________________________________________________
```

```
 Layer (type)                 Output Shape
=================================================
 input_2 (InputLayer)         [(None, 2, 22

 iaq_score_model (Sequential)  (None, 1)

 tm_score_model (Sequential)   (None, 1)

 add (Add)                    (None, 1)


=================================================
Total params: 575,204
Trainable params: 575,204
Non-trainable params: 0
_________________________________________________
```

```
final_generator = DataGenerator(batch_minimize_score, window_size=example_window, maxClose
```

```
model_scoring.compile(loss='mse', optimizer="adam", metrics=["mae"])
```

```
model_scoring.evaluate(final_generator)
```

```
100/100 [==============================] - 13
[76.08616638183594, 6.668454647064209]
```

```
def loss_by_combined_net(days, preds):
    input_to_model_iaq =  tf.stack([days, preds], axis=1)
    scoring = model_scoring(input_to_model_iaq)
    return tf.reshape(scoring, [-1])#flatten


# Predict with the model_scoring

decisions_axe = axe(example_day, window=example_window.numpy(), max_close=example_max_clos
decisions_dao = dao(example_day, window=example_window.numpy(), max_close=example_max_clos
decisions_all_closed = np.zeros(example_day.shape)

days = np.array([example_day, example_day, example_day])
decisions = np.array([decisions_axe, decisions_dao, decisions_all_closed])

print(loss_by_combined_net(days, decisions))
# print(minimize_loss(days, tf.cast(decisions,tf.bool)))
```

```
tf.Tensor([202.86726 200.20808 200.20808], sh
```

straightforward approch

We will now return to our original network and will train it a few epochs with the score network

```
classic_model.summary()
```

```
Model: "naive_model"
_________________________________________________________________
 Layer (type)                Output Shape              
=================================================================
 layer_normalization (LayerN  (None, 229)              
 ormalization)                                                   

 dense (Dense)               (None, 512)               

 reshape (Reshape)           (None, 512, 1)            

 conv1d (Conv1D)             (None, 489, 32)           

 flatten (Flatten)           (None, 15648)             

 dense_1 (Dense)             (None, 512)               

 dense_2 (Dense)             (None, 512)               

 dense_3 (Dense)             (None, 229)               

 lambda (Lambda)             (None, 229)               

=================================================================
Total params: 8,511,439
Trainable params: 8,511,439
Non-trainable params: 0
_________________________________________________________________
```

```
model2 = keras.Model(inputs=classic_model.input, outputs=classic_model.layers[-2].output)
model2.summary()
```

```
Model: "model_1"
_________________________________________________________________
 Layer (type)                Output Shape              
=================================================================
 layer_normalization_input (  [(None, 229)]            
 InputLayer)                                                     

 layer_normalization (LayerN  (None, 229)              
 ormalization)                                                   

 dense (Dense)               (None, 512)               

 reshape (Reshape)           (None, 512, 1)            

 conv1d (Conv1D)             (None, 489, 32)           

 flatten (Flatten)           (None, 15648)             
```

```
 dense_1 (Dense)             (None, 512)

 dense_2 (Dense)             (None, 512)

 dense_3 (Dense)             (None, 229)

=================================================
Total params: 8,511,439
Trainable params: 8,511,439
Non-trainable params: 0
_________________________________________________
```

```
model2.compile(loss=loss_by_combined_net, optimizer="adam")
model2.fit(X_train, X_train, batch_size = 64, epochs = epochs_base_const*20, validation_sp
```

```
Epoch 1/20
2/2 [==============================] - 2s 333
Epoch 2/20
2/2 [==============================] - 0s 33m
Epoch 3/20
2/2 [==============================] - 0s 28m
Epoch 4/20
2/2 [==============================] - 0s 32m
Epoch 5/20
2/2 [==============================] - 0s 26m
Epoch 6/20
2/2 [==============================] - 0s 26m
Epoch 7/20
2/2 [==============================] - 0s 25m
Epoch 8/20
2/2 [==============================] - 0s 27m
Epoch 9/20
2/2 [==============================] - 0s 26m
Epoch 10/20
2/2 [==============================] - 0s 26m
Epoch 11/20
2/2 [==============================] - 0s 31m
Epoch 12/20
2/2 [==============================] - 0s 47m
Epoch 13/20
2/2 [==============================] - 0s 29m
Epoch 14/20
2/2 [==============================] - 0s 29m
Epoch 15/20
2/2 [==============================] - 0s 28m
Epoch 16/20
2/2 [==============================] - 0s 31m
Epoch 17/20
2/2 [==============================] - 0s 30m
Epoch 18/20
2/2 [==============================] - 0s 28m
Epoch 19/20
2/2 [==============================] - 0s 30m
Epoch 20/20
2/2 [==============================] - 0s 26m
<keras.callbacks.History at 0x7f1ce254e290>
```

pretraining approch

Trying pre-training for the algorithm may help since it's not progressing much

```
# train model to allways open to start with
model2.compile(loss='binary_crossentropy', optimizer="adam")
allways_open = tf.ones(X_train.shape, dtype=X_train.dtype)
model2.fit(X_train, allways_open, batch_size = 64, epochs = epochs_base_const*2, validatio
```

```
Epoch 1/2
2/2 [==============================] - 1s 183
Epoch 2/2
2/2 [==============================] - 0s 24m
<keras.callbacks.History at 0x7f1ce21f5c10>
```

```
print(model2.predict(X_train))
```

```
[[0.56152904 0.5015973  0.44546068 ... 0.5308
 [0.56152904 0.5015973  0.44546068 ... 0.5308
 [0.56152904 0.5015973  0.44546068 ... 0.5308
 ...
 [0.56152904 0.5015973  0.44546068 ... 0.5308
 [0.56152904 0.5015973  0.44546068 ... 0.5308
 [0.56152904 0.5015973  0.44546068 ... 0.5308
```

```
model2.compile(loss=loss_by_combined_net, optimizer="adam")
```

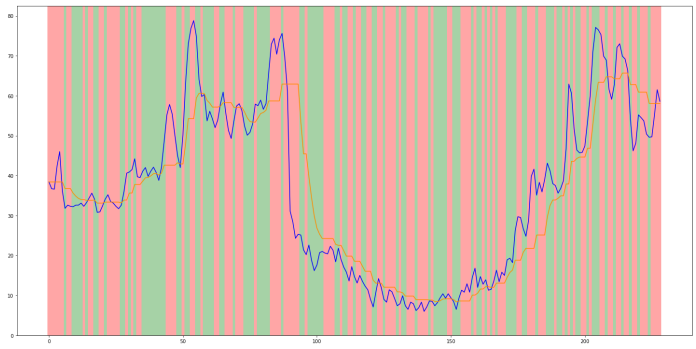
```
model2.fit(X_train, X_train, batch_size = 64, epochs = epochs_base_const*10, validation_sp
```

```
Epoch 1/10
2/2 [==============================] - 1s 314
Epoch 2/10
2/2 [==============================] - 0s 27m
Epoch 3/10
2/2 [==============================] - 0s 25m
Epoch 4/10
2/2 [==============================] - 0s 29m
Epoch 5/10
2/2 [==============================] - 0s 28m
Epoch 6/10
2/2 [==============================] - 0s 25m
Epoch 7/10
2/2 [==============================] - 0s 26m
Epoch 8/10
2/2 [==============================] - 0s 26m
Epoch 9/10
```

```
2/2 [==============================] - 0s 38m
Epoch 10/10
2/2 [==============================] - 0s 28m
<keras.callbacks.History at 0x7f1c806ad610>
```

```
def combined_network(day, window:int, max_close:int):
  return probabilities_to_boolean(model2.predict(tf.expand_dims(example_day,0))[0])


day_to_use = example_day

score, indoor_air, decisions = run_and_save_algo(combined_network, day_to_use)

print(score)
show(day_to_use, indoor_air, decisions)
```

```
0.9845611398344264
```



Reinforcement Learning

Self build policy gradient

policy gradient

```
gp_model = keras.models.Sequential([
    keras.layers.LayerNormalization(input_dim =day_length),
    keras.layers.Dense(512, activation="relu"),
    keras.layers.Reshape((-1,1)),
    keras.layers.Conv1D(filters=32, kernel_size=(example_window.numpy(),)),
    keras.layers.Flatten(),
    keras.layers.Dense(512, activation="relu"),
    keras.layers.Dense(512, activation="relu"),
    keras.layers.Dense(512, activation="relu"),
    keras.layers.Dense(day_length, activation="sigmoid")],
    name= "PG_net")
gp_model.summary()
iteration = 0
```

```
Model: "PG_net"
_________________________________________________________________
 Layer (type)                Output Shape              
=================================================================
 layer_normalization_3 (Laye  (None, 229)              
 rNormalization)                                                 

 dense_10 (Dense)            (None, 512)               

 reshape_1 (Reshape)         (None, 512, 1)            

 conv1d_1 (Conv1D)           (None, 489, 32)           

 flatten_2 (Flatten)         (None, 15648)             

 dense_11 (Dense)            (None, 512)               

 dense_12 (Dense)            (None, 512)               

 dense_13 (Dense)            (None, 512)               

 dense_14 (Dense)            (None, 229)               

=================================================================
Total params: 8,774,095
Trainable params: 8,774,095
Non-trainable params: 0
_________________________________________________________________
```

We will run the model on days, and take the outputs vector from the network, which represents the opening profitability at any given moment, and

convert the vector to absolute openings (meaning a bianry vector). We will run crossentropy between the profitability and the binary vector, this way we are theoretically telling the network "what you just did - is good", while at the same time "record" the gradient. We then will calculate the score that day would have received, and normalize it in relation to other scores, that way scores that are lower than avergae will receive a positive number around 1, and the scores that are above average will receive a negative number around -1. We will then multiply the normalized score by the gradients weights we saved. This tells the network to avoid weights that gave a relatively high score, and to move towards weights that gave a relatively low score.

```
#utility function
@tf.function(experimental_relax_shapes=True)
def multiply_each_grad_by_reward(grad, rewards):
  len = rewards.shape[0]
  grad_shape = tf.shape(grad)
  reshaped_grad = tf.reshape(grad,(len,-1))
  weighted_grad = rewards*reshaped_grad
  return tf.reshape(weighted_grad, grad_shape)
```

```
def get_iteration_step_func():
  # because optimizer creates variables when apply_gradients is called for the first time
  # refer to https://github.com/tensorflow/tensorflow/issues/27120#issuecomment-540071844
  @tf.function
  def iteration_step(data, model, optimizer, play_one_day_func, iteration = 0, buffer = No
    rewards, all_grads = tf.map_fn(lambda day: play_one_day_func(day, model), data, fn_out
    if buffer is not None: buffer.add_batch(rewards)
    all_rewards = buffer.gather_all() if buffer is not None else rewards

    mean = tf.reduce_mean(all_rewards)
    std = tf.math.reduce_std(all_rewards)
    min = tf.math.reduce_min(all_rewards)
    tf.print("Iteration: ", iteration, ", mean rewards: ", mean, ", std rewards: ", std, "
    normalized_rewards = (mean - rewards)/std #lower rewards will be positive numbers
    all_mean_grads = [tf.reduce_mean(multiply_each_grad_by_reward(grads, normalized_reward
    optimizer.apply_gradients(zip(all_mean_grads, model.trainable_variables))
  return iteration_step
```

```
@tf.function
def play_one_day(day, model):#normal
  day_as_batch = tf.expand_dims(day,0)
```

```
  with tf.GradientTape() as tape:
    open_proba = model(day_as_batch, training=True)
    actions = probabilities_to_boolean(open_proba, training=True)
    y_target = tf.cast(actions, DTYPE)
    main_loss = keras.losses.binary_crossentropy(y_target, open_proba)
  grads = tape.gradient(main_loss, model.trainable_variables)
  reward = minimize_loss(day_as_batch, actions)
  return reward, grads
```

Here too, we will begin training a network to open consistently

```
gp_model.compile(loss='binary_crossentropy', optimizer="adam")
allways_open = tf.ones(X_train.shape, dtype=X_train.dtype)
gp_model.fit(X_train, allways_open, batch_size = 64, epochs = epochs_base_const*1, validat
```

```
2/2 [==============================] - 1s 178
<keras.callbacks.History at 0x7f1c800a2e90>
```

```
buff = tf_uniform_replay_buffer.TFUniformReplayBuffer(data_spec=tf.TensorSpec([1], tf.floa
```

```
buff.data_spec
```

```
TensorSpec(shape=(1,), dtype=tf.float32, name
```

```
optimizer = keras.optimizers.Adam(learning_rate=1e-5, name='pg_opt')
```

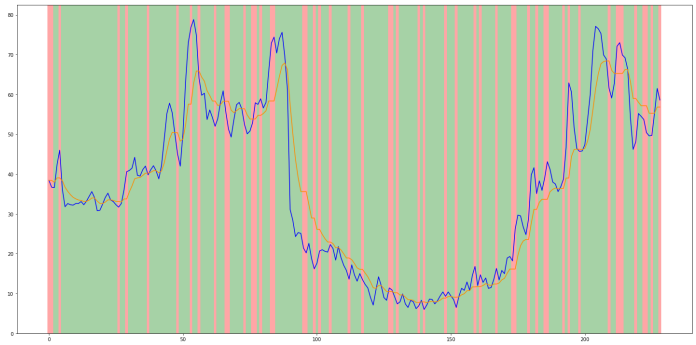
```
iteration_step = get_iteration_step_func()
for i in tf.range(epochs_base_const*29):
  iteration += 1
  iteration_step(X_train, gp_model, optimizer, play_one_day, iteration, buff)
```

```
WARNING:tensorflow:From /usr/local/lib/python
Instructions for updating:
Use `as_dataset(..., single_deterministic_pas
From /usr/local/lib/python3.7/dist-packages/t
Instructions for updating:
Use `as_dataset(..., single_deterministic_pas
Iteration:  1 , mean rewards:  68.4029312 , s
Iteration:  2 , mean rewards:  67.61306 , std
Iteration:  3 , mean rewards:  67.093071 , st
Iteration:  4 , mean rewards:  66.4581451 , s
Iteration:  5 , mean rewards:  65.9932098 , s
WARNING:tensorflow:5 out of the last 5 calls
5 out of the last 5 calls to <function get_it
Iteration:  6 , mean rewards:  65.4065857 , s
WARNING:tensorflow:6 out of the last 6 calls
6 out of the last 6 calls to <function get_it
Iteration:  7 , mean rewards:  64.8361359 , s
```

```
Iteration:  8 , mean rewards:  64.2608 , std
Iteration:  9 , mean rewards:  63.7433434 , s
Iteration:  10 , mean rewards:  63.2523918 ,
Iteration:  11 , mean rewards:  62.7734451 ,
Iteration:  12 , mean rewards:  62.2785034 ,
Iteration:  13 , mean rewards:  61.7773857 ,
Iteration:  14 , mean rewards:  61.2835884 ,
Iteration:  15 , mean rewards:  60.7983 , std
Iteration:  16 , mean rewards:  60.293045 , s
Iteration:  17 , mean rewards:  59.7719383 ,
Iteration:  18 , mean rewards:  59.2554054 ,
Iteration:  19 , mean rewards:  58.7521935 ,
Iteration:  20 , mean rewards:  58.2527924 ,
Iteration:  21 , mean rewards:  57.7666779 ,
Iteration:  22 , mean rewards:  57.2638512 ,
Iteration:  23 , mean rewards:  56.7773552 ,
Iteration:  24 , mean rewards:  56.3105659 ,
Iteration:  25 , mean rewards:  55.8731232 ,
Iteration:  26 , mean rewards:  55.4404945 ,
Iteration:  27 , mean rewards:  55.018795 , s
Iteration:  28 , mean rewards:  54.6068687 ,
Iteration:  29 , mean rewards:  54.2143974 ,
```

```
def self_build_policy_gradient(day, window:int, max_close:int):
    pred = gp_model.predict(day_to_use.reshape(1,-1))
    decisions = probabilities_to_boolean(pred[0], True)
    return decisions


day_to_use = example_day

score, indoor_air, decisions = run_and_save_algo(self_build_policy_gradient, day_to_use)

show(day_to_use, indoor_air, decisions)
display(f"self build policy gradient algorithm got score of {score} and is {'' if is_valid
```

```
'self build policy gradient algorithm got sc
ore of 0.9886888268363171 and is not folowin
g the standard'
```



Pointer Network

In the attached article it seems like using pointer networks produced good results, therefore we will try that as well.

create model

We will build the model according to the instructions in the article

```
class Attention(keras.layers.Layer):
  """Attention layer"""
  def __init__(self, hidden_dimensions, name='attention'):
    super().__init__(name=name, trainable=True)
    self.W1 = keras.layers.Dense(hidden_dimensions, use_bias=False)
    self.W2 = keras.layers.Dense(hidden_dimensions, use_bias=False)
    self.V = keras.layers.Dense(1, use_bias=False)

  def call(self, encoder_outputs, dec_output, mask=None):
    w1_e = self.W1(encoder_outputs)
    w2_d = self.W2(dec_output)
    tanh_output = keras.activations.tanh(w1_e + w2_d)
    v_dot_tanh = self.V(tanh_output)
    if mask is not None:
        v_dot_tanh += (mask * -1e9)
    attention_weights = keras.activations.softmax(v_dot_tanh, axis=1)
    att_shape = K.shape(attention_weights)
    return K.reshape(attention_weights, (att_shape[0], att_shape[1]))


class Decoder(keras.layers.Layer):
  """Decoder class for PointerLayer"""
```

```
    def __init__(self, hidden_dimensions):
      super().__init__()
      self.lstm = keras.layers.LSTM(hidden_dimensions, return_sequences=False, return_state=

    def call(self, x, hidden_states):
      dec_output, state_h, state_c = self.lstm(x, initial_state=hidden_states)
      return dec_output, [state_h, state_c]

    def get_initial_state(self, inputs):
      return self.lstm.get_initial_state(inputs)

    def process_inputs(self, x_input, initial_states, constants):
      return self.lstm._process_inputs(x_input, initial_states, constants)


  class PointerLSTM(keras.layers.Layer):
    """PointerLSTM"""

    def __init__(self, hidden_dimensions, name='pointer', **kwargs):
      super().__init__(name=name, **kwargs)
      self.hidden_dimensions = hidden_dimensions
      self.attention = Attention(hidden_dimensions)
      self.decoder = Decoder(hidden_dimensions)

    def call(self, x, training=None, mask=None, states=None):
      """
      :param Tensor x: Should be the output of the encoder
      :param Tensor states: last state of the encoder
      :param Tensor mask: The mask to apply
      :return: Pointers probabilities
      """
      time_d_length = K.shape(x)[1]
      en_seq = x
      x_input = x[:, -1, :]
      x_input = K.repeat(x_input, time_d_length)

      if states:
          initial_states = states
      else:
          initial_states = self.decoder.get_initial_state(x_input)

      constants = []
      preprocessed_input, _, constants = self.decoder.process_inputs(x_input, initial_states
      constants.append(en_seq)
      last_output, outputs, states = K.rnn(self.step, preprocessed_input,
                                           initial_states,
                                           go_backwards=self.decoder.lstm.go_backwards,
                                           constants=constants,
                                           input_length=time_d_length
                                          )

      return outputs

    def step(self, x_input, states):
      x_input = K.expand_dims(x_input,1)
```

```
    _, [h, c] = self.decoder(x_input, states[:-1])

    en_seq = states[-1]
    time_d_length = K.shape(en_seq)[1]
    dec_seq = K.repeat(h, time_d_length)
    probs = self.attention(dec_seq, en_seq)
    return probs, [h, c]

  def get_output_shape_for(self, input_shape):
    # output shape is not affected by the attention component
    return (input_shape[0], input_shape[1], input_shape[1])

  def compute_output_shape(self, input_shape):
    return (input_shape[0], input_shape[1], input_shape[1])
```

try it on

```
hidden_size = 128


main_input = keras.layers.Input(shape=(None, 1), name='main_input')
encoder, state_h, state_c = keras.layers.LSTM(hidden_size, return_sequences = True, return
decoder = PointerLSTM(hidden_dimensions=hidden_size, name="decoder")(encoder,states=[state

ptr_model = keras.Model(main_input, decoder, name = 'pointer_model')
ptr_model.summary(120)
```

```
Model: "pointer_model"
_____________________________________________
 Layer (type)                          Output
=============================================
 main_input (InputLayer)               [(None

 encoder (LSTM)                        [(None
                                        (None
                                        (None

 decoder (PointerLSTM)                 (None,



=============================================
Total params: 231,040
Trainable params: 231,040
Non-trainable params: 0
_____________________________________________
```

The network returns a pointer, therefore we will create functions that convert it to decisions.

```
@tf.function
def pointers_to_boolean(pointers_array, training = None): #get_action
    max_val = tf.reduce_max(pointers_array, axis = -1, keepdims = True)
    return tf.equal(pointers_array, max_val)
@tf.function
def boolean_pointer_to_decision(pointers_array):
  return tf.reduce_any(pointers_array, axis = 1)
```

The following method is similar to the method in the previous section - policy gradient with feed forward neural network

```
@tf.function
def play_one_day_pointer(day, model):#pointer
  day_as_batch = tf.expand_dims(day,0)
  with tf.GradientTape() as tape:
    pred = model(day_as_batch, training=True)
    pointers = pointers_to_boolean(pred, training=True)
    y_target = tf.cast(pointers, DTYPE)
    main_loss = keras.losses.binary_crossentropy(y_target, pred)
  grads = tape.gradient(main_loss, model.trainable_variables)
  actions = boolean_pointer_to_decision(pointers)
  reward = minimize_loss(day_as_batch, actions)
  return reward, grads
```

```
optimizer = keras.optimizers.Adam(name="ptr_opt")
```

```
buff = tf_uniform_replay_buffer.TFUniformReplayBuffer(data_spec=tf.TensorSpec([1], tf.floa
iteration_step = get_iteration_step_func()
```

```
buff.data_spec
```

```
TensorSpec(shape=(1,), dtype=tf.float32, name
```

The next cells are commented out till we will figure out the problem related to the "play_one_day".

```
# gp_model.trainable_variables[0].shape
```

```
# ptr_model.trainable_variables[0].shape
```

```
# reward_gp, grads_gp = play_one_day(X_train[0], gp_model)
reward_ptr, grads_ptr = play_one_day_pointer(X_train[0], ptr_model)
```

```
reward_ptr
```

```
<tf.Tensor: shape=(1,), dtype=float32, numpy=
```

```
# reward_gp.shape
```

```
# grads_gp[0].shape
```

```
# reward_ptr.shape
```

```
# grads_ptr[0].shape
```

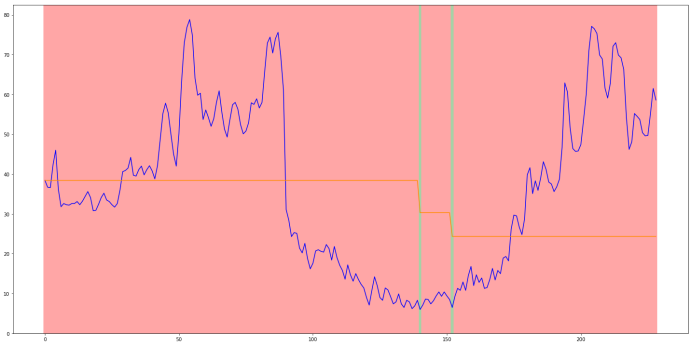
```
for iteration in tf.range(epochs_base_const*1):
  iteration_step(X_train, ptr_model, optimizer, play_one_day_pointer, iteration, buff)
```

```
Iteration:  0 , mean rewards:  207.057816 , s
```

```
def pointers_network(day, window:int, max_close:int):
  return boolean_pointer_to_decision(pointers_to_boolean(ptr_model.predict(tf.expand_dims(
```

```
day_to_use = example_day

score, indoor_air, decisions = run_and_save_algo(pointers_network, day_to_use)

show(day_to_use, indoor_air, decisions)
display(f"self build policy gradient algorithm got score of {score} and is {'' if is_valid
```

```
'self build policy gradient algorithm got sc
ore of 0.916003031469541 and is not folowing
the standard'
```



tf-agent

We will use (somewhat degenerately) the built-in infrusctructure of the tensorflow for reinforcement learning. We will create an environment that casts a polluted day and expects a desicions vector from the network, and returns a reward that is the obtained score.

```
class OracelEnv(environments.py_environment.PyEnvironment):

    def __init__(self, shape = (229,)):
        self._shape = shape
        self._action_spec = tf_agents.specs.BoundedArraySpec(shape=self._shape, dtype=np.i
        self._observation_spec = tf_agents.specs.ArraySpec(shape=self._shape, dtype=np.flo
        self._state = example_day.astype(np.float32)
        self._episode_ended = True

    def action_spec(self):
        return self._action_spec

    def observation_spec(self):
        return self._observation_spec

    def _reset(self):
        self._state = example_day.astype(np.float32)
        self._episode_ended = False

        return time_step.restart(self._state)

    def _step(self, action):
        if self._episode_ended:
            # The last action ended the episode. Ignore the current action and start
```

```
            # a new episode.
            return self.reset()
        self._episode_ended = True #it's one step game
        boolean_actions = tf.cast(action, tf.bool)
        reward = tf_maximize_score(self._state, boolean_actions, example_window, example_m
        return time_step.termination(self._state, reward=reward)

environments.utils.validate_py_environment(OracelEnv())
train_env = environments.tf_py_environment.TFPyEnvironment(OracelEnv())


num_iterations = 250
collect_episodes_per_iteration = 2
replay_buffer_capacity = 2000

fc_layer_params = (512,)*5

learning_rate = 1e-4
log_interval = 25
num_eval_episodes = 10
eval_interval = 50
```

We will define a network

```
actor_net = tf_agents.networks.actor_distribution_network.ActorDistributionNetwork(
    train_env.observation_spec(),
    train_env.action_spec(),
    fc_layer_params=fc_layer_params)
```

We will create an agent

```
# optimizer = keras.optimizers.Adam(learning_rate=learning_rate)
optimizer = tf.compat.v1.train.AdamOptimizer(learning_rate=learning_rate)

train_step_counter = tf.Variable(0)

tf_agent = agents.reinforce.reinforce_agent.ReinforceAgent(
    train_env.time_step_spec(),
    train_env.action_spec(),
    actor_network=actor_net,
    optimizer=optimizer,
    normalize_returns=True,
    train_step_counter=train_step_counter)
tf_agent.initialize()
```

We will define policies

```
eval_policy = tf_agent.policy
collect_policy = tf_agent.collect_policy
random_policy = random_tf_policy.RandomTFPolicy(train_env.time_step_spec(), train_env.acti
```

We will define a storage buffer

```
replay_buffer = tf_uniform_replay_buffer.TFUniformReplayBuffer(
    data_spec = tf_agent.collect_data_spec,
    batch_size = train_env.batch_size,
    max_length = replay_buffer_capacity
    )
```

We will define metrics

```
train_metrics = [
 metrics.tf_metrics.MaxReturnMetric(),
 metrics.tf_metrics.MinReturnMetric(),
 metrics.tf_metrics.AverageReturnMetric(),
]
```

We will collect a few random rounds so that we give a point of reference to the agents performance

```
collect_driver = tf_agents.drivers.dynamic_episode_driver.DynamicEpisodeDriver(
    train_env,
    random_policy,
    observers = [replay_buffer.add_batch] + train_metrics,
    num_episodes = num_iterations)


final_time_step, final_policy_state = collect_driver.run()
```

```
for i in train_metrics:
     print(i.name,i.result())
```

```
     MaxReturn tf.Tensor(-191.01956, shape=(), dty
     MinReturn tf.Tensor(-207.01393, shape=(), dty
     AverageReturn tf.Tensor(-201.79733, shape=(),
```

```
dataset = replay_buffer.as_dataset(
 sample_batch_size=64,
 num_steps=2,
 num_parallel_calls=3).prefetch(3)
```

```
     WARNING:tensorflow:From /usr/local/lib/python
```

```
 Instructions for updating:
 Use `as_dataset(..., single_deterministic_pas
 From /usr/local/lib/python3.7/dist-packages/t
 Instructions for updating:
 Use `as_dataset(..., single_deterministic_pas
```

```
collect_driver.run = tf.function(collect_driver.run)
tf_agent.train = tf.function(tf_agent.train)
```

```
def train_agent(n_iterations):
    time_step = None
    policy_state = tf_agent.collect_policy.get_initial_state(train_env.batch_size)
    iterator = iter(dataset)
    for iteration in range(n_iterations):
        time_step, policy_state = collect_driver.run(time_step, policy_state)
        trajectories, buffer_info = next(iterator)
        train_loss = tf_agent.train(trajectories)
        tf.print(f"\r{iteration} loss:{train_loss.loss.numpy():.5f}", end="")
    print('\n')
#         if iteration % log_interval == 0:
#             for i in train_metrics:
#                 print(i.name,i.result())
```

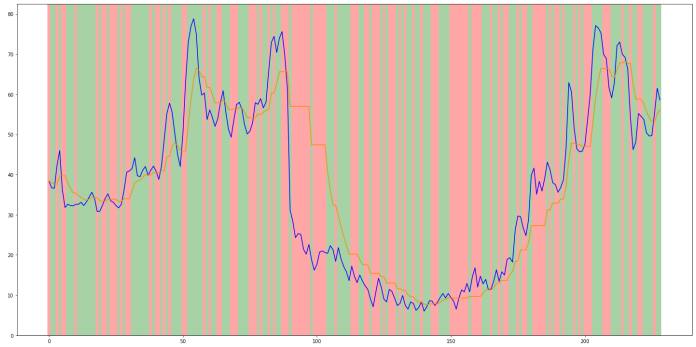
```
train_agent(epochs_base_const*1)
for i in train_metrics:
    print(i.name,i.result())
```

```
 0 loss:-157.38034

 MaxReturn tf.Tensor(-176.986, shape=(), dtype
 MinReturn tf.Tensor(-206.99496, shape=(), dty
 AverageReturn tf.Tensor(-198.2834, shape=(),
```

```
def tf_agent_call_function(day, window:int, max_close:int):
    """
    This function is used to get teh results from the "tf_agent".
    """
    asdf_dataset = replay_buffer.as_dataset(
      num_parallel_calls=3).prefetch(3)

    iterator = iter(asdf_dataset)
    trajectories, buffer_info = next(iterator)

    time_step = tf_agents.trajectories.TimeStep(
        step_type=trajectories.step_type,
        reward=trajectories.reward,
        discount=trajectories.discount,
        observation=trajectories.observation
    )
    preds = tf_agent.policy.action(time_step)
```

```
    return preds.action


day_to_use = example_day

score, indoor_air, decisions = run_and_save_algo(tf_agent_call_function, day_to_use)

show(day_to_use, indoor_air, decisions)
display(f"tf-agent got score of {score} and is {'' if is_valid_closed(decisions, example_w
```

```
'tf-agent got score of 1.0252807666710155 an
d is not folowing the standard'
```



tensorforce

```
# This flag is a hack to allow full run of the notebook without remove the tensorforce cod
# There is some packages dependency versions issue with other packages, so we are not runn
is_should_run_tensorforce = False
```

We tried using a package where the majority of the parameters are predefined. We built the environment similarly to the tf-agents

```
if is_should_run_tensorforce:
  class OracelEnvironment(Environment):

    def __init__(self, shape = (229,)):
      super().__init__()
      self._shape = shape

    def states(self):
      return dict(type='float', shape=self._shape)

    def actions(self):
      return dict(type='bool', shape=self._shape)

    def reset(self):
      self._state = example_day#np.random.uniform(0, 100, size = self._shape)
      return self._state

    def execute(self, actions):
      terminal = True
      reward = tf_maximize_score(self._state, actions, example_window, example_max_close)
      self._state = example_day#np.random.uniform(0, 100, size = self._shape)
      return self._state, terminal, reward.numpy()
```

```
if is_should_run_tensorforce:
  environment = Environment.create(environment=OracelEnvironment)
```

We created an agent the is supposed to know independently which network architecture is preferable

```
if is_should_run_tensorforce:
  agent = Agent.create(
```

```
        agent='tensorforce', environment=environment, update=64,
        optimizer=dict(optimizer='adam', learning_rate=1e-4),
        objective='policy_gradient', reward_estimation=dict(horizon=20),
        exploration = dict(type='linear', unit='episodes', num_steps=1000, initial_value=1.,
        )


if is_should_run_tensorforce:
  runner = Runner(
      agent=agent,
      environment=environment
  )


if is_should_run_tensorforce:
  runner.run(num_episodes=1000)



if is_should_run_tensorforce:
  runner.run(num_episodes=100, evaluation = True)



if is_should_run_tensorforce:
  day_to_use = example_day

  score, indoor_air, decisions = run_and_save_algo("?", day_to_use)

  show(day_to_use, indoor_air, decisions)
  display(f"tensorforce got score of {score} and is {'' if is_valid_closed(decisions, exam
```

Summarize

Following is a summary of the project:

1. The oracle tell
    - The problem we faced and the solution we tried.
    - Input and output data shapes.
    - Explanation of the methods we used
2. Comparison of the methods we used
    - Graph comparison
    - Results open-close graph all algorithems
3. Summary of our project work process and the lessons learned

The oracle tell

The problem we faced and the solution we tried

The problem we chose for our work was defined by data. Its solution has the potential to save lives. Here is a summary of the work process and the results:

The problem we faced:

Our general goal was to find the optimal balance at every given moment of the day between closing the fresh-air system to prevent air-pollution from entering the building and opening the system to allow entrance of fresh air.

Input and output data shapes:

Given a graph of the Outdoor Air Quality (OAQ), find the optimal sequence of opening/closing the ventilation of a building, to optimize the Indoor Air Quality (IAQ).

Explanation of the methods we used:

A. Which method did we use?

B. What was the result?

C. What was limiting us in this way and how could it be improved - more computation time, more data, improvements in the algorithm, etc.

We took several approaches during the project:

1. Classic algorithms, which are very useful as a starting point but far from optimal and give an idea why the problem is not simple.
2. Genetic algorithm, which shows that by combining randomness and computational power, it is possible to achieve results that are competitive with traditional methods.
3. Deep learning: To find a solution to the problem, deep learning has been used in various ways.

Deep learning methods:

1. Initially, we tried the classic method, entering data and giving it a score in hopes that the network would get there on its own.
    - In this approach, instead of using a classic loss function, we use the score given by the openings as the loss function.
    - Results: This approach failed since the loss function is either non-derivative or has a derivative of zero regarding the commands. That is, the loss function acts as a "stair function" of some sort.
2. As mentioned before, the method of directly using the score function as a loss function did not work. Therefore, in order to create a loss function that is derivative, we will train networks that will mimic the loss function and use them as a loss function.
    - The score calculation is composed of two parameters: First, the number of times we violated the regulation by closing the ventilation. Second, the amount of pollution we prevented. Since direct training did not work, we will try a slightly different training approach. We built two networks, each mimicking a function, and then combined them together as layers in an integrated funcional model.
    - Results: We didn't succeded to overfit the network to our needs, so we guess we could not use it. (If the network can't overfit on a preticular set of data, it can't predict the general case...)
3. Reinforcement Learning - Self build policy gradient

- We implemented a policy gradient algorithm and used that to solve the problem.
- Results: Network convergence did not produce good results

4. Reinforcement Learning - Pointer network
    - Based on an article we saw, we tried some policy gradient infrastructure using another network architecture, that might be a better option.
    - Results: The network's training time was really long and its performance wasn't very good
5. Reinforcement Learning - tf-agent
    - TF provides a built-in policy gradient infrastructure that we tested.
    - Results: Resulted in no results. The agent didn't succeded to learn the first step of the problem of the regulation policy.
6. Reinforcement Learning - tensorforce
    - Tensorforce provides a reinforcement learning infrastructure that should be very automatic.
    - Results: Resulted in no results

Comparison of the methods we used

Let us stop here and gather the results of the work we have done and make conclusions.

In the next section we will compare the results for each algorithm. We will refer in the summary only to the results that bore fruit, That is, bring about minimal results that are worth reference - better than the trivial algorithm of DOA.

For the algorithms that did not bear fruit we will explain why we think we did not reach the results.

Graph comparison

After all that work of trail and error, let's try to put it all toghter into graphs, that will help use to understand the strangth of each strategy. The graphs will help to compare easily between the different algorithms.

Scores graph

Compares the scores that the different algorithms have achieved.

Remainder: The score is the ratio of the total indor polution to the outdor total polution (and include regulation vaiolations as punish to this score).

This is an explanation of the scoring:

Algorithms that provide results compliant with regulatory restrictions will receive a score in this range: (-1, 0).

An algorithm that violates regulatory restrictions will receive a score that is lower than -1, which is the range (-infaty, -1).

An optimal algorithm will receive a score closest to 0 (from below).

General overview of the graphs

1. The graph shows that the deep learning algorithms failed to account for the regulatory constraints, which resulted in bad scores. Without studying the limitations of regulation, an algorithm will not work because it cannot be used. The pollution saving scores of these algorithms weren't optimal, but even if they were, we couldn't use them because of the regulatory violations (it is unfair to obtain a good score if regulations can be broken. for

example, run the "AXE" algorithm without maintaining the regulations).

2. For the same day we are working with, the learning algorithm and the genetic algorithm return different results for different runs. In other words, the result is not deterministic. A large part of this result is due to the fact that we use random data to train the deep learning algorithms, which is created using a generator we have developed. It is not surprising that genetic algorithms consistently return different results since their results are determined by randomness.

Algorithms with the best results

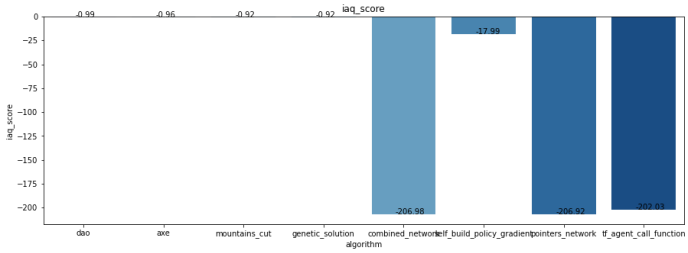
These algorithms produced the best scores: Mountain_cut and Genetic Algorithm. Both received a score of -0.92 which means the air inside would be eight percent cleaner than the air outside if they were used. Mountain_cut always produces the same result, whereas Genetic_algorithm gets better the deeper we go into the generations. In the case of genetic algorithms, we cannot ensure that increasing the number of generations indefinitely will result in the optimal outcome since it may be that we "fall" to a local minimum from which the algorithm does not succeed.

```
# the commented code is if we want to add more scores stats
def compare_stats(df_data: 'pd.DataFrame', field_name: 'str', title: 'str', palette_color:

  # fig, (ax1, ax2, ax3) = plt.subplots(1, 3, sharey=True, figsize=(16, 8))
  fig, (ax1) = plt.subplots(1, 1, figsize=(15, 5), sharey=True)

  # score:
  sns.barplot(ax=ax1, x="algorithm", y=field_name, data=df_data, palette=palette_color)
  ax1.set_title(title)

  for i, v in enumerate(zip(df_data[field_name])):  # , ars_results, avg)):
      ax1.text(i - 0.1, v[0] + 0.01, str(round(v[0], 2)))
```

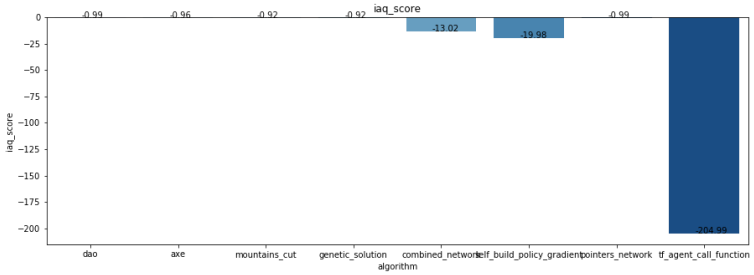
```
    # Show the final plot
    plt.show()
df_score = pd.DataFrame(algorithms_scores.items(), columns=['algorithm', 'iaq_score'])
display(df_score)
compare_stats(df_score, field_name="iaq_score", title="iaq_score", palette_color="Blues")
```

```
---------------------------------------------
-------------------------------
AttributeError
Traceback (most recent call last)
/usr/local/lib/python3.7/dist-
packages/IPython/core/formatters.py in
__call__(self, obj)
    332                 pass
    333             else:
--> 334                 return printer(obj)
    335             # Finally look for
special method names
    336             method =
get_real_method(obj, self.print_method)

                    3 frames
/usr/local/lib/python3.7/dist-
packages/pandas/io/formats/format.py in
to_html(self, buf, encoding, classes,
notebook, border)
    986         encoding: str | None = None,
    987         classes: str | list | tuple
| None = None,
--> 988         notebook: bool = False,
    989         border: int | None = None,
    990         table_id: str | None = None,

AttributeError: 'NotebookFormatter' object
has no attribute 'get_result'

SEARCH STACK OVERFLOW
```

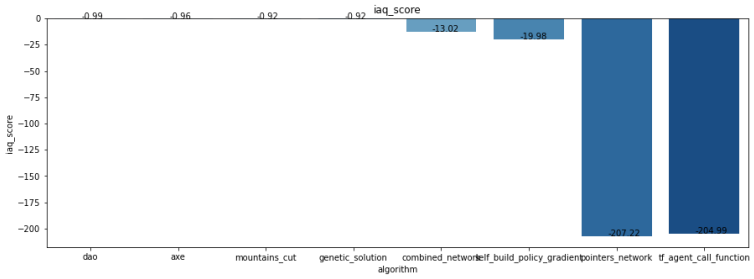
	algorithm	iaq_score
0	dao	-0.993654
1	axe	-0.958058
2	mountains_cut	-0.923345
3	genetic_solution	-0.921735
4	combined_network	-206.984561
5	self_build_policy_gradient	-17.988689
6	pointers_network	-206.916003
7	tf_agent_call_function	-202.025281



Full run of the notebook: #1



Full run of the notebook: #2



Time duration graph

Compare the time duration that the different algorithms took to run (Not the learning time, still we will talk about the learning time in this section).

This is an explanation of the scoring:

The algorithm runtime is less important to us, yet it is a handy and easy parameter to compare through.

It is optimal to get the runtime closest to zero.

General overview of the graphs

1. The graph shows that the results of the deep learning algorithms take longer than that of the classical algorithms. This is not surprising.
2. The classic algorithms will run at a fixed time (according to the computer you're using) every time we run them on the same data, and it does not matter how much time we add to them.

3. Learning algorithms consider time as an important factor in their output. Perhaps the network will perform better if we train it more? We might get better results if we allow more generations in the genetic algorithm? At some point, the learning algorithms converged to a certain value and the network was unable to learn "more". As for the genetic algorithm, we tried all sorts of different parameters for the number of generations or probability of mutation, but we did not achieve much better results, so we will assume the algorithm has reached its maximum potential here as well.

Algorithms with the best results

Not surprisingly, the classic algorithms produced better results for run time, but they were not meaningful in terms of solving the problem.

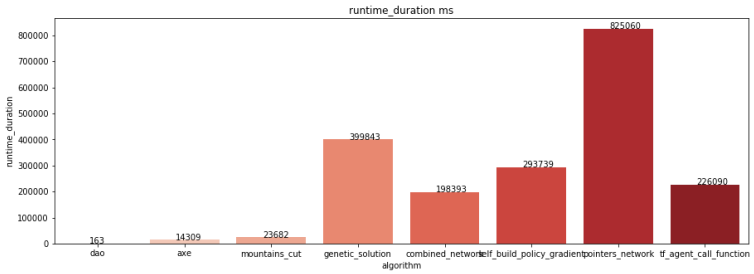
```
df_runtime_duration = pd.DataFrame(algorithms_runtime_duration.items(), columns=['algorith
display(df_runtime_duration)
compare_stats(df_runtime_duration, field_name="runtime_duration", title="runtime_duration
```

```
------------------------------------------
------------------------------
AttributeError
Traceback (most recent call last)
/usr/local/lib/python3.7/dist-
packages/IPython/core/formatters.py in
__call__(self, obj)
    332                 pass
    333             else:
--> 334                 return printer(obj)
    335             # Finally look for
special method names
    336             method =
get_real_method(obj, self.print_method)
```

3 frames

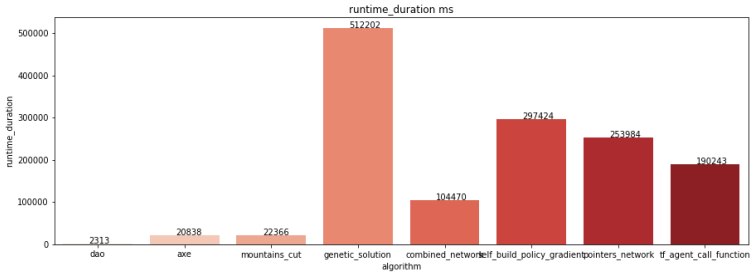
```
/usr/local/lib/python3.7/dist-
packages/pandas/io/formats/format.py in
to_html(self, buf, encoding, classes,
notebook, border)
    986         encoding: str | None = None,
    987         classes: str | list | tuple
| None = None,
--> 988         notebook: bool = False,
    989         border: int | None = None,
    990         table id: str | None = None,
```

Full run of the notebook: #1




```
4               combined_network                1518
```

Full run of the notebook: #2



Results open-close graph all algorithems

Compare the output results the different algorithms produced.

This is an explanation of the scoring:

This comparison does not have a score. By visually analyzing the obtained graphs, we will describe briefly the differences observed.

Comparing the graphs makes it very easy to understand what each algorithm does, and leads to a more in-depth understanding of how each algorithm can be improved.

We chose to display results of two different runs of the notebook, to show the difference obtained for the learning algorithms.

Analyses of classical algorithms

Because the algorithms are deterministic, the results are the same in both runs. As can be seen from the graph, each of the classical algorithms provides a slight improvement to the problem, but they do not fully resolve it.

Among the classic algorithms, the best is:
Mountains_cut

An example for Mountains_cut's solutions not being optimal can be seen in the fifth peak to the right, where the algorithm allows ventilation to be open, despite a higher level of pollution there than it did with earlier closures. One could argue that earlier closures result in greater pollution savings, which is true, but not relevant to the Mountains_cut algorithm because it doesn't factor in this parameter.

Analyses of Genetic algorithm

Examining the images from the two different runs, it is apparent that the algorithm does return non-deterministic results, meaning that each run is different.

It was very easy for the algorithm to study the regulatory limitations. In approximately 50 generations, we observe that the algorithm has an average score of (-1.0), which is a valid openness-closing result.

We saw a slight improvement after training for another 50 generations, but not more (subsequent generations: 100-500 did not improve the algorithm's results).

A comparison of the results of the Genetic_algorithm algorithm with the Mountains_cut algorithm reveals that most of the places that it is obvious the algorithm needs to close were occupied (all the "peaks" in the pollution outside).

In some cases, the closures appear during the middle of the day when the pollution outside is at a low point, so it's clear that if we open them, we can close them later when the pollution begins to rise, thus improving the score of choice. The likelihood of a mutation in opening or closing the "correctness" is relatively low. Maybe if we add more generations to the algorithm, we will be able to improve its performance? We tried it and it didn't changed.

Analyses of Learning algorithm

Observing pictures from the two different runs, we can see that the algorithms acquired different things from each run.

The **combined_network** algorithm learned that it should open all the time to avoid regulatory penalties, and tried to close at the edges, which resulted in a -13 (see blue graph).

As for **self_build_policy_gradient**, there is indication that it considered the regulations, but not fully understand it. Nor did it examine "peaks" of pollution problems. The algorithm seems to have chosen randomly what to open and close, and failed to learn and improve.

pointers_network seems to not work, as it didn't learned the regulation.

```
**tf_agent_call_function** seems to
```

```
def show_all_graphs(working_algorithms, algorithms_decisions):
    row_count = (len(working_algorithms)+1)//2
    fig, axes = plt.subplots(row_count, 2, figsize=(50,30))
    # axes: ((ax1, ax2, ax3), (ax4, ax5, ax6))

    for ax_number, algo_name in zip(range(len(working_algorithms)), working_algorithms):
      i, j = (ax_number)//2, (ax_number)%2
      print(f"algo={algo_name}, ax_number={ax_number}, i={i}, j={j}")
      score, indoor_air = iaqScore(day_to_use, algorithms_decisions[algo_name])
      fill_ax_for_ploting_decisions(axes[i][j], example_day, indoor_air, algorithms_decisi
      axes[i][j].set_title(algo_name, fontweight ="bold", fontsize=40)

    fig.tight_layout()


for i in algorithms_decisions:
  print(i)
```

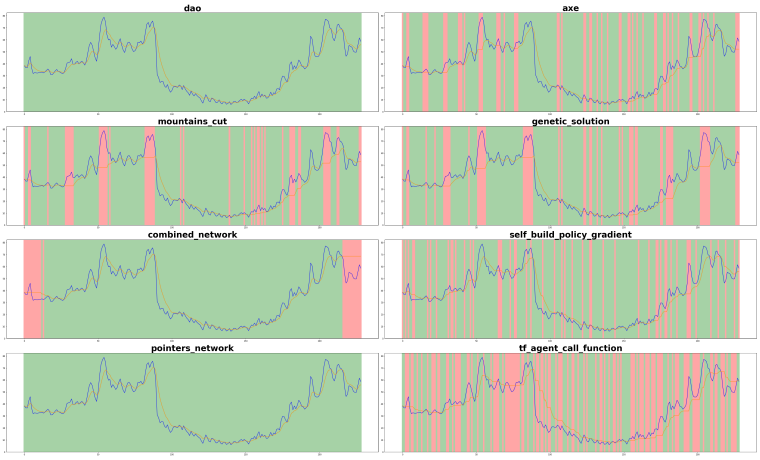
```
 dao
 axe
 mountains_cut
 genetic_solution
 combined_network
 self_build_policy_gradient
 pointers_network
 tf_agent_call_function
```

```
working_algorithms = ["dao",
                      "axe",
                      "mountains_cut",
                      "genetic_solution",
                      "combined_network",
                      "self_build_policy_gradient",
                      "pointers_network",
                      "tf_agent_call_function"]

show_all_graphs(working_algorithms, algorithms_decisions)
```

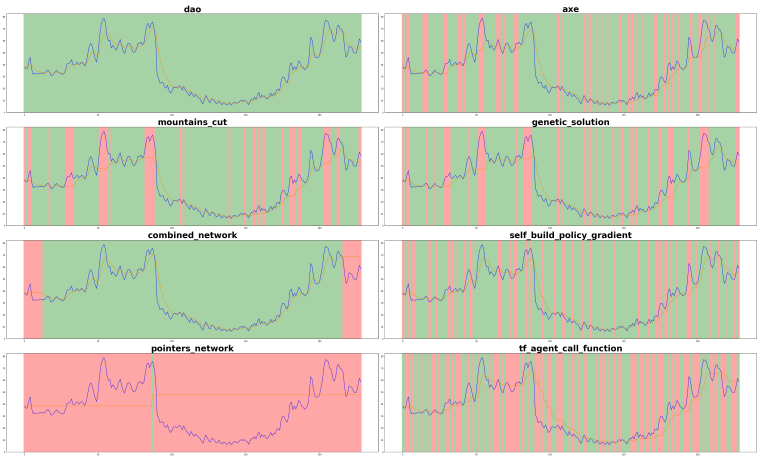
```
algo=dao, ax_number=0, i=0, j=0
algo=axe, ax_number=1, i=0, j=1
algo=mountains_cut, ax_number=2, i=1, j=0
algo=genetic_solution, ax_number=3, i=1, j=1
algo=combined_network, ax_number=4, i=2, j=0
algo=self_build_policy_gradient, ax_number=5,
algo=pointers_network, ax_number=6, i=3, j=0
algo=tf_agent_call_function, ax_number=7, i=3
```

The next cell show a comparison between all the working algorithms:

Full run of the notebook: #1



Full run of the notebook: #2



Summary of our project work process and the lessons learned

What did the results turn out like and did we get a satisfactory result?

Despite our best efforts, we were not able to solve the problem. It was our expectation that a neural network (deep learning) would be able to provide a more comprehensive solution to the problem, but in practice we were not able to train a network to produce good results for a single day, which is the beginning of solving the general problem.

Based on the scope of our work, the genetic algorithm was the most appropriate choice. Due to its flexibility, it can accept any day and any set of constraints, and we can always trust it to provide a reasonable solution. As a disadvantage, it takes a long time to run every time, and if on the way he chooses a route that leads to a local minimum, it is difficult to get out of it. As well, the algorithm is not deterministic. Different runs will result in different results, even for the same restrictions and day.

What new tools did we learn?

1. Python notebooks, google colab: for colabrative work.
2. Genetic algorithm
3. tensorflow.keras
4. tf_agents: tensorflow RL framework.
5. Combinatorial problem-solving approaches
6. **visualisation:** The importance of visualisation to understand the problem and the solution.

Which tricks did we learn?

1. Create a generator to simulate data.
2. To engage the problem from different angle every time that things not going well.
3. That improvments to the runtime of the training make life better.
4. To play with the hyper-parameters can change the results of the network.
5. You can use ANN as the loss function for other ANNs.

Working together

Rea:

My partner Chai taught me a great deal, and whenever I was in despair I knew talking to him would be helpful, both mentally and practically. The pace of work was problematic, and I take responsibility for a large part of it. In some areas, I could have been more systematic and organized. Despite my good intentions to work on the project, I sometimes lacked the practical ability to actually implement it. I learned a lot from this project, and also from working with Chai. As we talked about what needed to be done, we seemed to have a common understanding, and I enjoyed working together. Thank you, Chai.

Chai:

I had great belife in the project, and really wanted to solve the problem we chosed. I'm a bit disapointed