Implementing AI-powered Semantic Character Recognition in Motor Racing



MARCH 2020

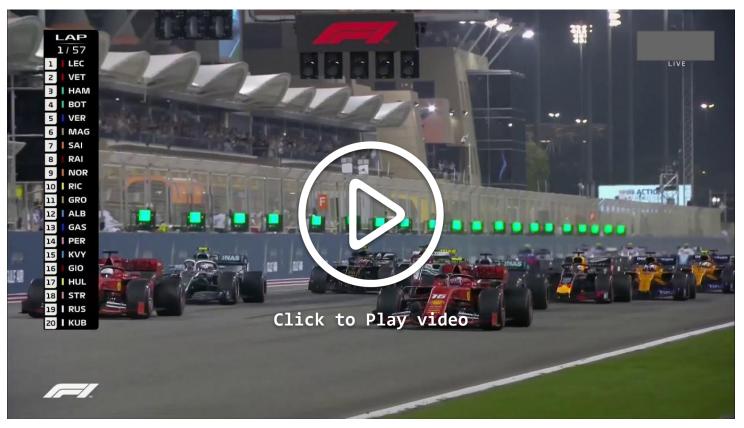
Jesús Hormigo David Albarracín

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GT RACER

GTRACE

Typical race start in television



Can you identify who is who?

A race start with augmented context



Isn't this more understandable now?

<u>1.- Manually</u>

A well trained human could potentially point and click to manually set the tags on every scene.

The challenge is that during live production in TV broadcasting, where shots are typically between 2-3 secs long, TV operators can't be fast enough to point and click, nor to add by hand any tags in a consistent way.

2.- With advanced technical solutions involving GPS









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BASE STATION ANTENNAS

House data-gathering computers, rendering machines, network hubs, video feeds, monitors and audio equipment that an eight-to-ten man crew converts into real time graphics using software.

GLOBAL POSITIONING SATELLITES

Track the positions of the racers via a small antenna mounted in each car's roof.

BASE STATION ANTENNAS Relay the data from the cars to the production tracks. They are mounted on top of the grandstands and on camera platforms on the back stretch. There are usually between four and eight, depending on track geometry.

SPEEDWAY

Base Station locations

RACETRACK

CAMERAS

4 Track and record positions of cars to create images that are sent to the production trucks through cables. There are six cameras positioned at strategic areas around the track to provide the best possible angles for using the system pointer graphics feature.

END RESULTS The final graphics are sent out for television, internet and wireless devices



* Example of the pointer feature that follows the car in real time



2 UNBOARD COMPOLER Collects telemetry data

(such as speed, throttle, brake, gears, g-force, A.P.M., etc) and streams it five times per second through the car's antennae to a series of base stations.

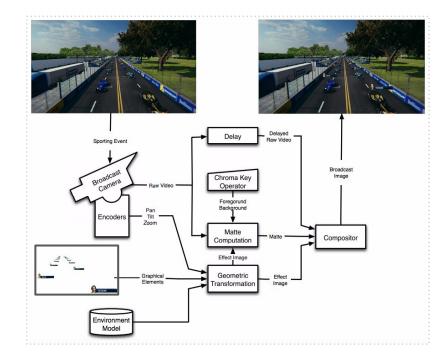






However, this solution have some cons:

- Complex technical implementation
- High operational costs
- Expensive electronics including RTK GPS (with a reference base station) for every car
- Kilometers (or miles :-]) of cable wired to each base station throughout the whole circuit
- Cameras with special "base" positioned at strategic areas around the track to provide the best possible angles and not valid with every shot
- Onboard cameras are not possible to be tracked even with the above methodology

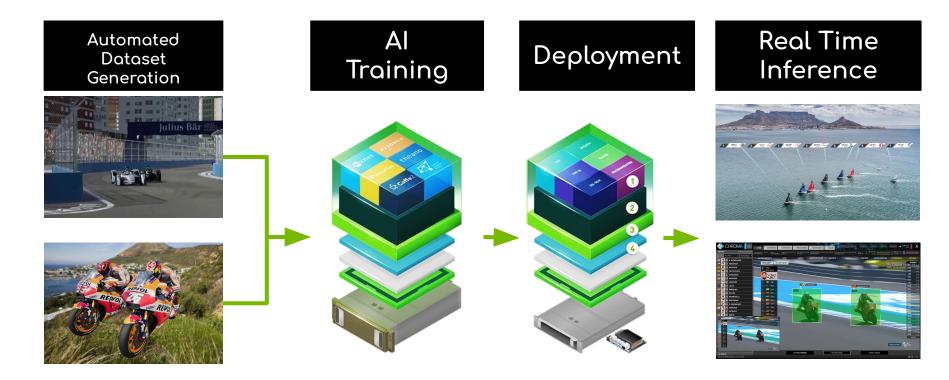


3.- With Neural Networks

We developed an autonomous system that <u>trains itself</u> on synthetic data based on a FBX model and <u>infers in real time</u>.

This way we can augment the context of scenes automatically and at a very low cost of implementation and operation.

Our Approach - Automated training and RT Inference



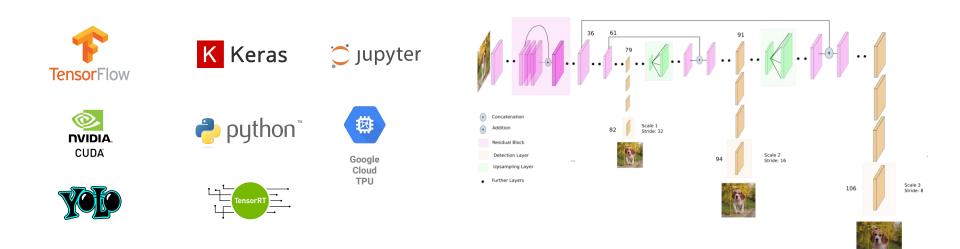
The challenges

- Lighting conditions are variable during the day
 In some series the car models have exactly the same shape and only have changing the liveries
- Inference has to be in REAL TIME as few frames later is too late to be used
- Matching specific standards in connectors and delivery of picture in HD

Let's deep dive into the details

- The Neural network architecture
- Synthetic dataset generation
- Training the neural network
- ✤ The inference
- The API
- The operator's User Interface
- The results
- Next generation neural network

The Neural Network



Real data is expensive to produce, sometimes dangerous and biased. There is no availability of real images before the first race and is a work intensive task with not enough footage to train the neural network and generate a good model.

In addition to this, almost no team races during testing with the final liveries.

Traditional workflow requires:

- Tagging precision
- Time to deliver
- Dataset preparation
- Data augmentation

The Training - 100% Synthetic training

Synthetic labels are automatic and accurate and extremely useful for training, in addition to validation

Our workflow consists of:

- Semi-automated tagging of real images
- Generation of synthetic images with latest changes
- Fine tuned training pipeline
 - Freeze most convolutional blocks and train only front-end from scratch
 - Train whole network loading pre-trained weights
- Distribution of dataset: training validation
- Mixing synthetic and real images for better usability
 - More detections pass threshold
 - Rise of accuracy metric around 15%

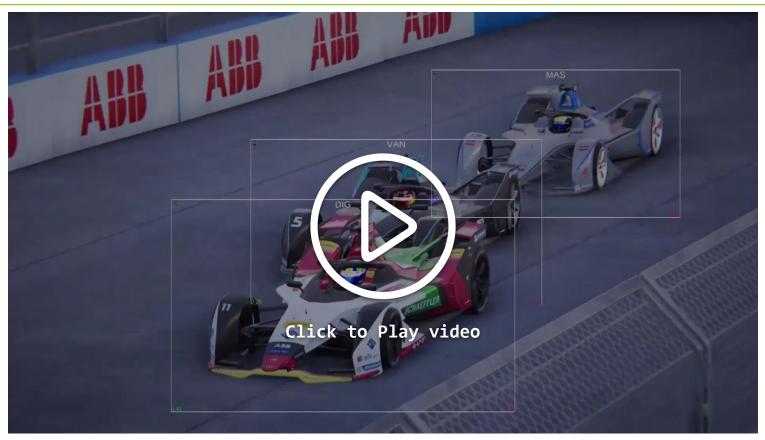
Lighting conditions affects detection



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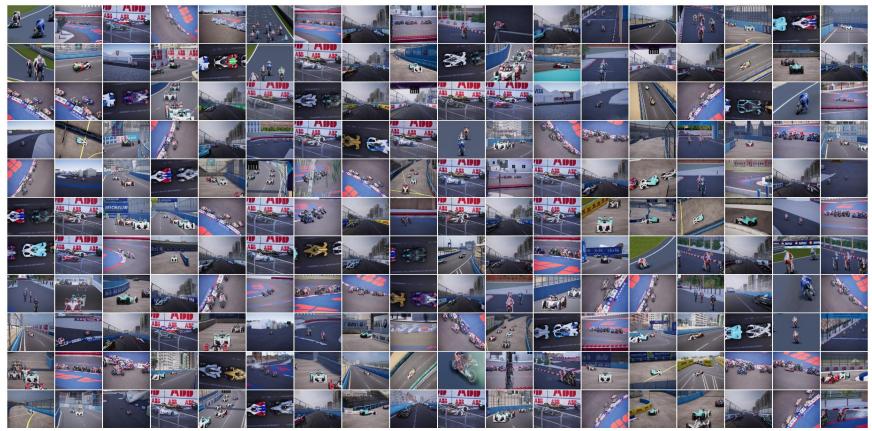
The Training - Synthetic image generation



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The Training - Our Synthetic DataSet



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The Training - DataSet building

def load_bboxes(annot_data, annot_format, filter_conf, invertYAxis):

```
# Return list
bounding_boxes = []
```

if annot_format.startswith('Synth1819'):

```
for bbox in annot_data['BoundingBoxList']:
```

Retrieving data

driver = bbox['Driver']
car_bb = bbox['Car_percent_in_bb']
oth_bb = bbox['Other_cars_percent_in_bb']
x_fix = bbox['Fixed_bb']['x']
y_fix = bbox['Fixed_bb']['y']
w_fix = bbox['Fixed_bb']['width']
h fix = bbox['Fixed_bb']['height']

```
# Getting combinated area reduction coefficient
comb_coef, bbox_factor = combined_area_reduction_coef(bbox, filter_conf)
```

```
# Parsing bbox params to VOC format
bounding_box = {
    'label': driver,
    'xmin': x_fix,
    'ymin': y_fix,
    'xmax': (y_fix + w_fix),
    'car_percent_in_bb': car_bb,
    'other_cars_percent_in_bb': oth_bb,
    'combined_area_reduction_coef': comb_coef,
    'bbox factor': bbox factor
```

}

```
if 'CarVisibleRatio' in bbox:
    bounding_box['CarVisibleRatio'] = bbox['CarVisibleRatio']
```

```
bounding_boxes.append(bounding_box)
```

def filtering(imageshape, bboxes, filter_conf):

Load parameters and prepare data

...

```
# Return list
filtered_bboxes = []
```

For each bbox run filtering
for idx, bbox in enumerate(bboxes):

Filter 1: Other Cars In Bounding Box # If bbox comes with this additional data, meaning, if the # bbox was generated synthetically, then we can filter if ('car_percent_in_bb' in bbox.keys() and 'other_cars_percent_in_bb' in bbox.keys() and 'combined_area_reduction_coef' in bbox.keys()):

Getting data from bbox car_in_bb = bbox['car_percent_in_bb'] oth_in_bb = bbox['other_cars_percent_in_bb'] comb_area_coef = bbox['combined_area_reduction_coef']

```
car_check = car_in_bb > min_car_in_bb
oth_check = oth_in_bb < max_other_cars_in_bb
comb_a_check = comb_area_coef > min_comb_area_coef
```

```
if not (car_check and oth_check and comb_a_check):
    continue
```

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We passed!
filtered_bboxes.append(bbox)

return filtered_bboxes

The Inference during Live Broadcasting

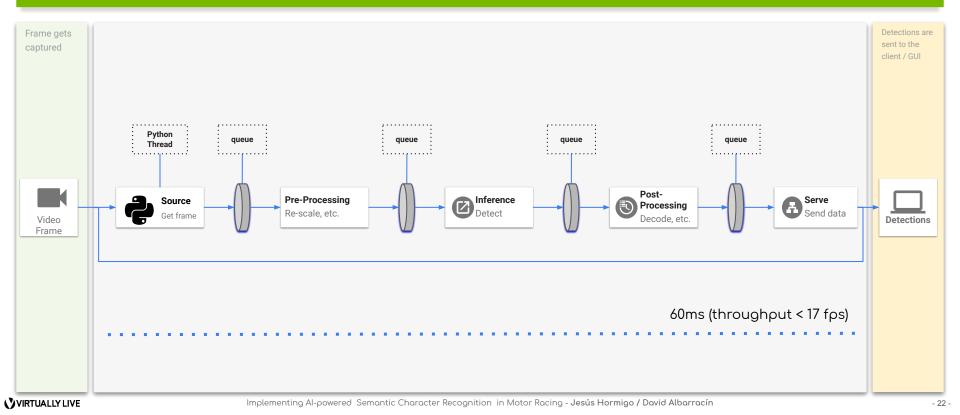
RMULA-E

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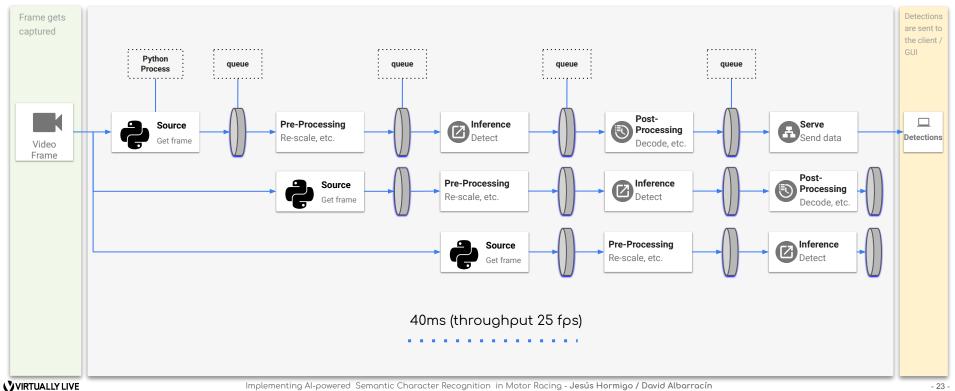
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Envision

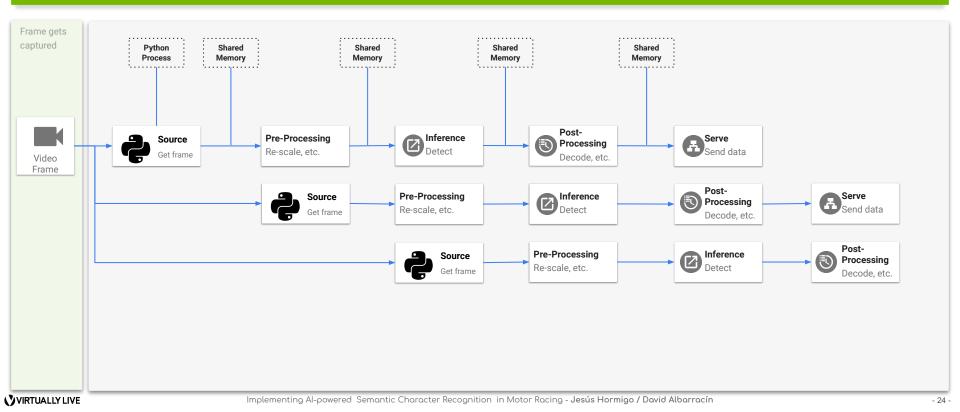
· Python · Multi-thread · Initial delay: 320ms (8 frames) · Throughput: 17 fps



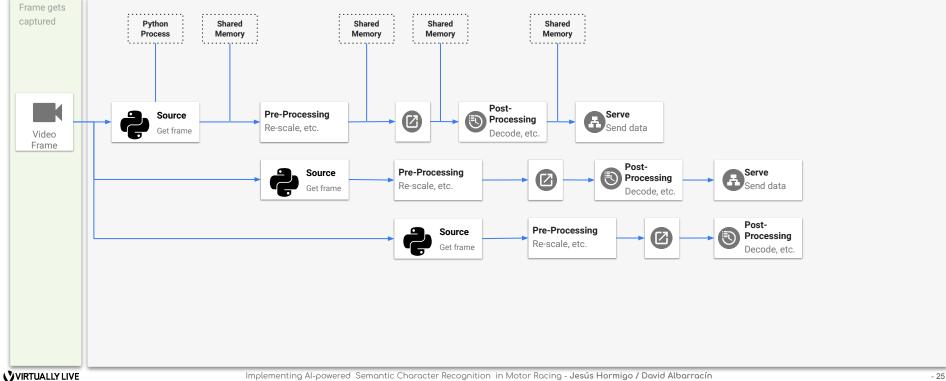
· Python · Multiprocessing · Actual parallelism · Big overhead in communications



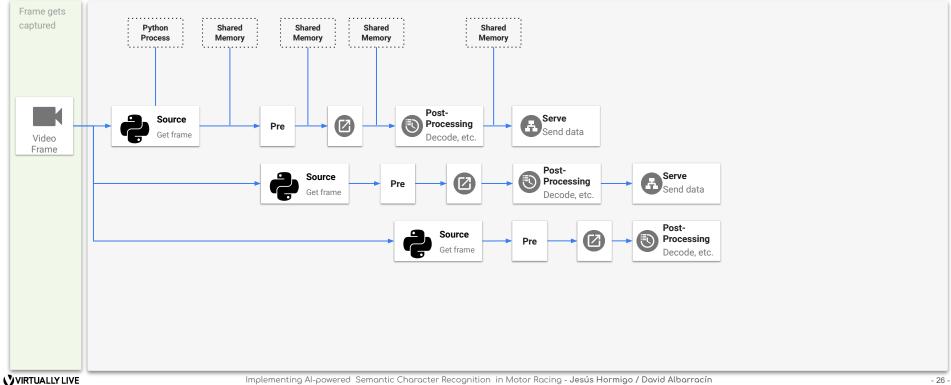
· Python · Multiprocessing · Shared memory buffers



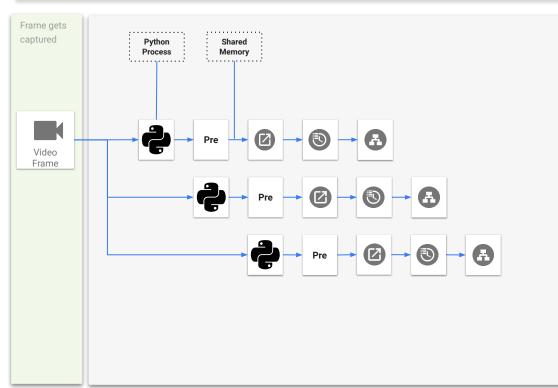
Inference: C++ bindings & TensorRT



Pre-Processing: C++ bindings & optimize operations

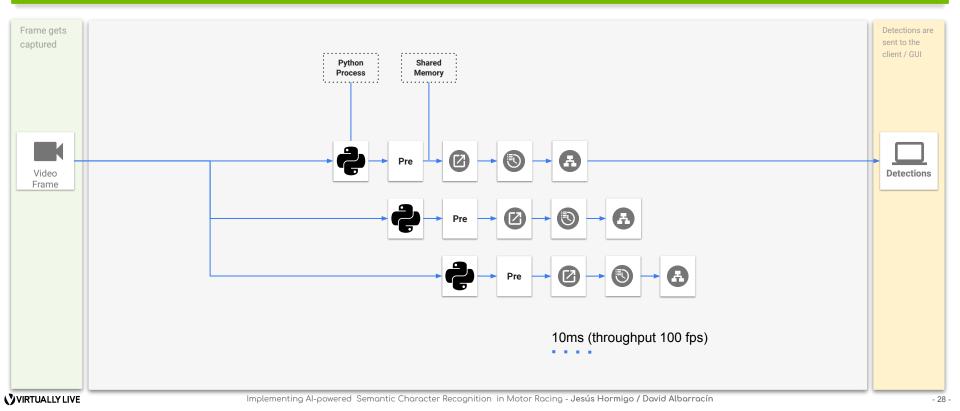


Post-Processing: C++ bindings & vectorize



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· Initial delay: 30ms (< 1 frame) · Throughput: 100 fps



```
def inference(conf, lock, barrier,...):
   """Reads from inference queue, do inference, queue into postprocessing queue"""
   # Synchronism at the beginning all processes should be initialized
   # before going into the main loop
   lock.acguire()
   # Three possible engines: keras, TensorFlow (executing a frozen graph
   # from keras directly in tf), TensorRT
   if conf['inferencer']['engine'] == 'TRT': # TensorRT
       lib = load lib(conf['TRT']['lib'])
       manager = RawNNRT(lib,...)
       def predict_tensorrt(model, batch_input):
           model.run network(batch input)
       predict = predict tensorrt
   elif conf['inferencer']['engine'] == 'TF': # TensorFlow
   else: # keras
   with manager as model:
       # Wait forever for new gueue elements
       while True:
           batch_output = predict(model, batch_input)
```

based on nvidia's reimplementation of pjreddie's darknet

from ctypes import *

••

```
def load_lib(libpath="libnn_raw_wrapper.so"):
    return CDLL(libpath, RTLD_GLOBAL)
```

```
class RawNNRT:
```

Stateful wrapper on the RT C++ inferencer so it can be used in a "with" statement """

```
def __init__(self, lib, ... ):
    self.lib = lib
```

```
def __enter__(self):
    """initialize the system at the beginning of the "with" statement"""
```

```
def __exit__(self, t, v, tb):
    """destroy the system when getting out of the "with" statement"""
```

```
def run_network(self, img):
    """img must be an array of float32, in format (batchSize, width, height,
    nchannels), all of these being members of self.raw[0]"""
```

```
self.naw[0].base.input_data = img.ctypes.data_as(c_float_p)
if self.callback_buffer_free:
    self.start_infer_naw(self.naw)
    self.end_infer_naw(self.raw)
else:
    self.infer_naw(self.raw)
if self.buffer_owner:
    self.copy_output(self.raw_results)
    results = [[x[0].transpose((1,2,0))] for x in self.raw_results]
    return results
```

```
••
```

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The Inference - The results



Reduced Form Factor Setup

Highly portable (for hostile environments), real time: **25 FPS** Inference delay: **3 frames** Output: fill & key signals



Pointers v3 Setup

Very powerful: **100 FPS** Inference Delay: **0 frames** Output: mixed video (clean + graphics) or fill & key signals

The API interface - Human configuration

Inference server



User Interface



... 2020-03-04 14:02:30,269 core send_data_to_client [INFO] Client accept timed out 2020-03-04 14:02:30,269 inferencer server [INFO] Frame 2057 throughput[FPS] 62.50 delay[s] 0.02 srcl 0.015588 srcW 0.015588 pret 0.015588 preW 0.000000 infl 0.015588 infW 0.007581 posl 0.015588 posW 0.000000 DAM(1.0), SHT_CHG = False 2020-03-04 14:02:30,301 core send_data_to_client [INFO] Client accept timed out 2020-03-04 14:02:30,301 inferencer server [INFO] Frame 2058 throughput[FPS] 31.98 delay[s] 0.03 srcl 0.015717 srcW 0.015717 pret 0.015717 preW 0.000000 infl 0.031271 infW 0.007588 posl 0.031271 posW 0.000000 BIR(0.994), SHT_CHG = True 2020-03-04 14:02:30,316 inferencer server [INFO] Frame 2059 throughput[FPS] 62.50 delay[s] 0.03 srcl 0.015554 srcW 0.015554 pret 0.015554 preW 0.000000 infl 0.015621 infW 0.007574 posl 0.015621 posW 0.000000 BIR(0.99), SHT_CHG = False 2020-03-04 14:02:30,332 core send_data_to_client [INFO] Client accept timed out 2020-03-04 14:02:30,332 core send_data_to_lent [INFO] Client accept timed out 2020-03-04 14:02:30,332 core send_data_to_lent [INFO] Client accept timed out 2020-03-04 14:02:30,332 core send_data_to_lent [INFO] Client accept timed out 2020-03-04 14:02:30,332 core send_data_to_lent [INFO] Client accept timed out 2020-03-04 14:02:30,332 core send_data_to_lent [INFO] Client accept timed out 2020-03-04 14:02:30,332 inferencer server [INFO] Frame 2060 throughput[FPS] 62.50 delay[s] 0.03 srcl 0.015621 srcW 0.015621 pret 0.015621 preW 0.000000 infl 0.015621 infW 0.007574 posl 0.015621 posW 0.000000 BIR(0.994), SHT_CHG = False ...

SDI Output graphics

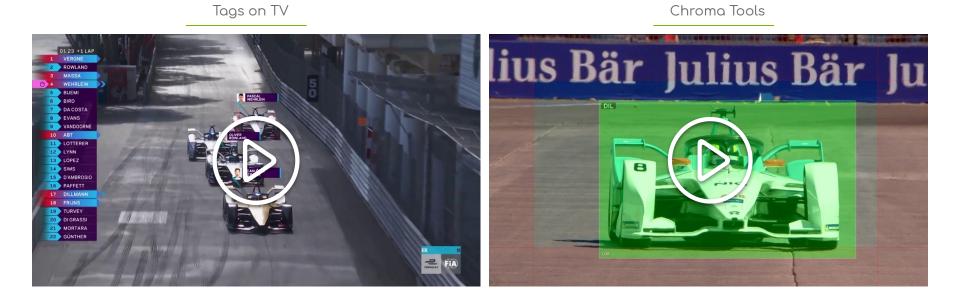


The User Interface

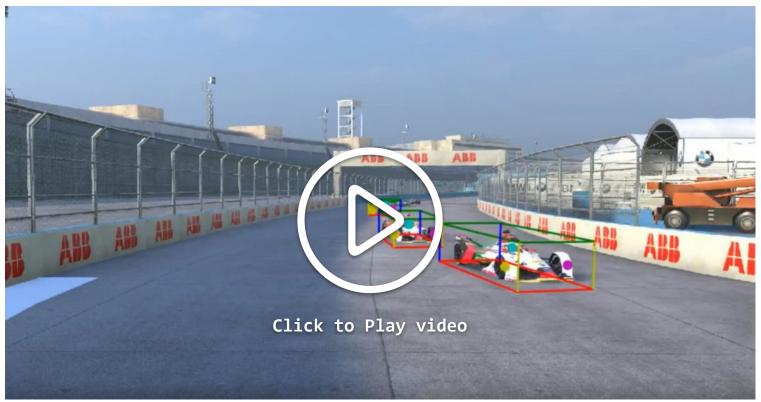


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The Results



Next generation of synth training and inference



Absolute Positional Tracking: object geometry and components of the car

Thank you!



JESÚS HORMIGO CTO

jesus@virtuallylive.com ♥ @jesushormigo



DAVID ALBARRACÍN Lead Research Engineer

dalbarracin@virtuallylive.com



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