



DC&N, BDS

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GenATC: Advancing Safety and Efficiency for Autonomous & Manned Vehicles



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Objective: Create autonomous ATC where human controllers are augmented with AI to help route both manned and unmanned aircraft occupying commercial airspace.

Approach: Create Model of Experts (MOE) Large Language Model fine tuned to handle ATC tasks including proactive communications with pilots on approach, departure, taxi, and flyover based on transponder data & predicted trajectory. Design digital twin of commercial airport and model traffic in and out in order to demonstrate safe autonomous and manned aircraft operation, increased capacity and anomaly resolution.

Benefit: Advanced insight into commercial autonomous aircraft design and legacy aircraft augmentation including transponder design. Demonstrate how Boeing products play a pivotal role in enhancing ATC capacity in both manned and unmanned products

Boeing Proprietary

Boeing Gen-Twin ATC (GT-ATC)

Gen-AI for Air Traffic Control Enhancement: Advancing Safety and Communication Efficiency for Autonomous & Manned Vehicles

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Outline

- Introduction/Motivation
- Related Works & Limitations
- Problem Statement
- Proposed System Architecture
 - Digital Twin
 - LLM
- Proposed Timeline
- Acknowledgment
- References



Introduction

- The International Traffic Association predicts that the quantity of travelling passengers would exceed 4 billion post 2024
 - ATC task: Scheduling flights locally, in the air and on the ground, for coordinated taxing
 - ATC goal: Provide maximum capacity, with most feasible efficiency
 - ATC staff: End up interacting and monitor up to thirty planes over a single time interval
- Deep interest in research on the use of AI in ATC
 - Reduced workload
 - Enhanced scheduling and efficiency
 - Improve management and monitoring
- AI models could be used:
 - Monitoring and Schedule Flights
 - Crew management
 - Flight routing

Related Works & Limitations

- AeroBERT [Ray et al.]
 - Explores potential of using ChatGPT to identify human factors issues from ASRS reporting
 - No preventative measure has been considered. Focuses on safety reporting and analyses
- AviationGPT [Wang et al.]
 - Explores potential use of fine-tuned model on aviation datasets for report querying
 - No real-world live environment testing considered.
- ATCO2 [Gomez et al.]
 - Evaluates the impact of domain shift on speech to text conversation of communication
 - Shows improved performance yet challenging given the pre training and fine tuning phases
- Real world gas turbine anomaly detection [Ma, Y. et al.]
 - Implements prototype of Turbine Uncertain Performance in a Digital Twin
 - Comparisons are used to generate predictions based on the detected anomalies

Challenges

- Most of the studies solely focus on:
 - Translation
 - Issue classification
 - Small subsystem consideration
- No preventative measure
 - Complexities involved in applying generative AI in ATC settings
 - Limited research addressing these challenges through NLP
- No evaluation in the use of models for
 - Decision making
 - Monitoring and analytical data collection
- Datasets do not provide the context in which events are happened
 - Sparse or limited sources data



Problem Statement

Critical demand for:

- Digital Twin of an Airport
 - To collect the context in which decisions are made
 - Simulate context changes in which the decisions are made
- Robust Generative AI Models
 - Make decisions
 - Monitor operations
 - Present predictive suggestions
 - Perform analytics
 - Provide preventative measures



Objectives

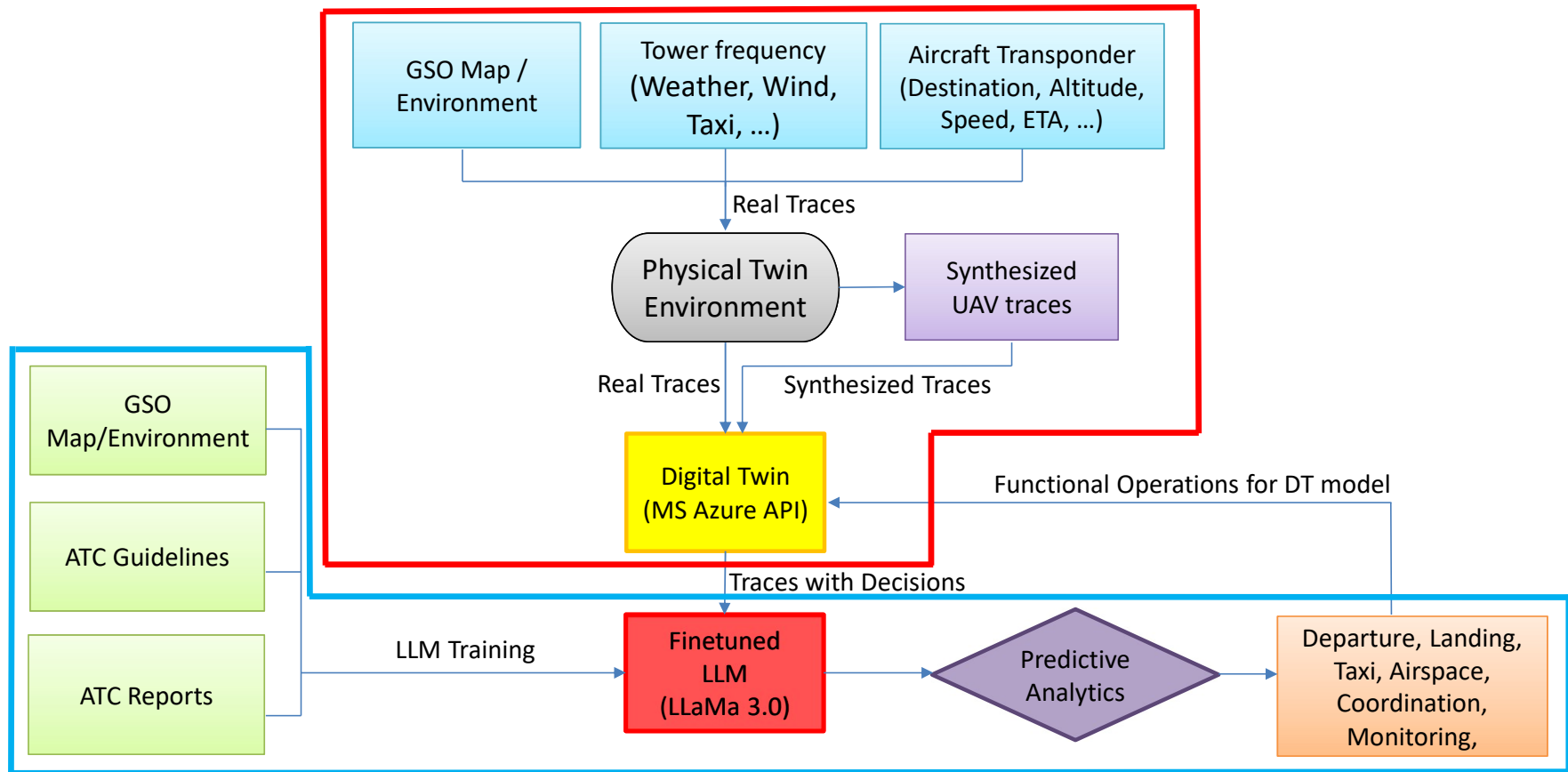
Develop a Digital Twin of GSO airport:

- Generate a digital twin of a real local airport
- Simulate different scenarios and collect required data
 - The context in which the operation will happen
 - The changes in the existing context
 - Decisions made based on the running context
 - Utilize Digital twin for LLM deployment and testing

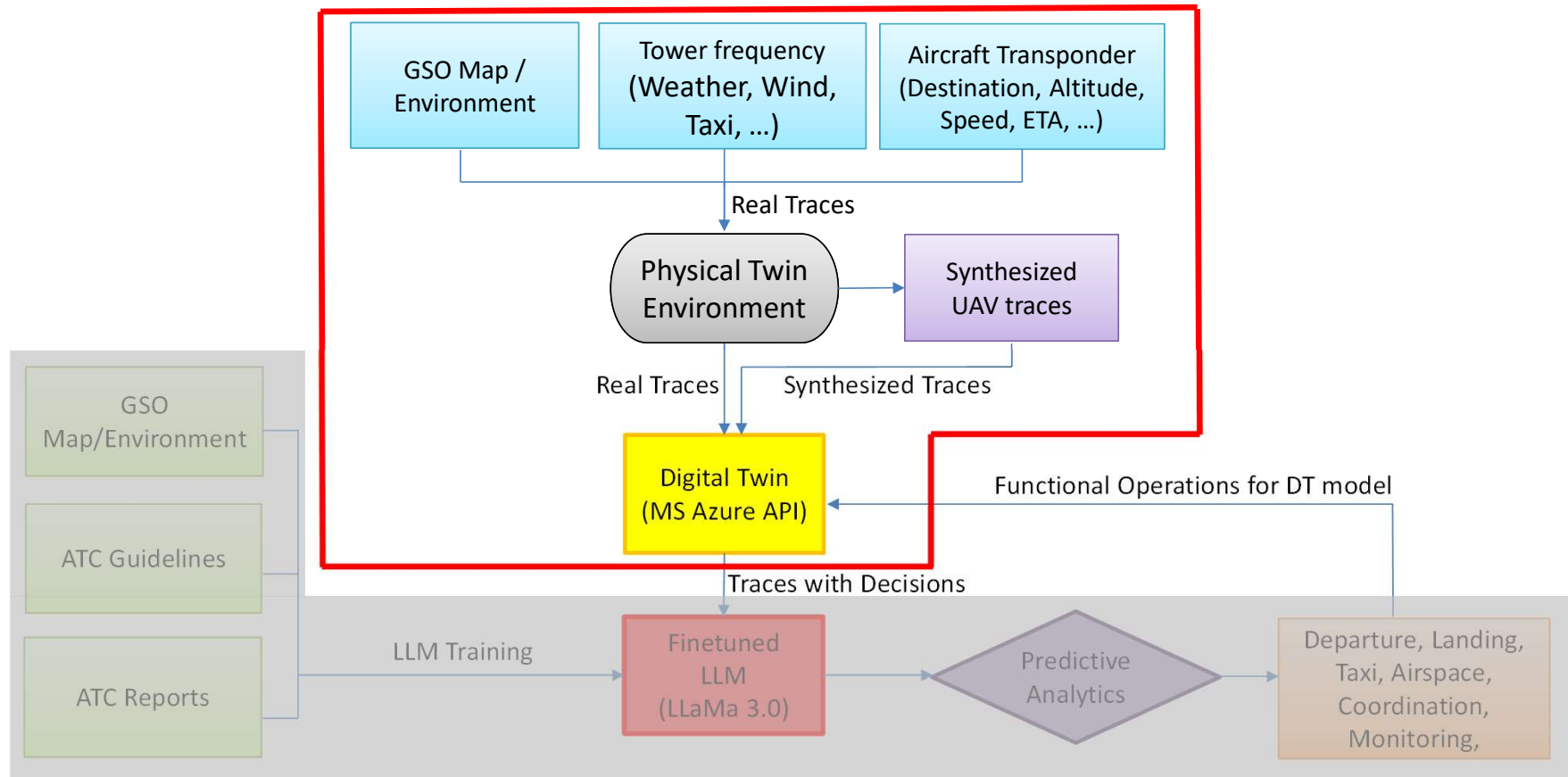
Train an LLM:

- Understand operations and the required procedure
- Can learn from the existing context and the decisions have been made
 - Navigating air traffic for automation
 - React to changes in the conditions
 - Detect issues

Proposed System Architecture



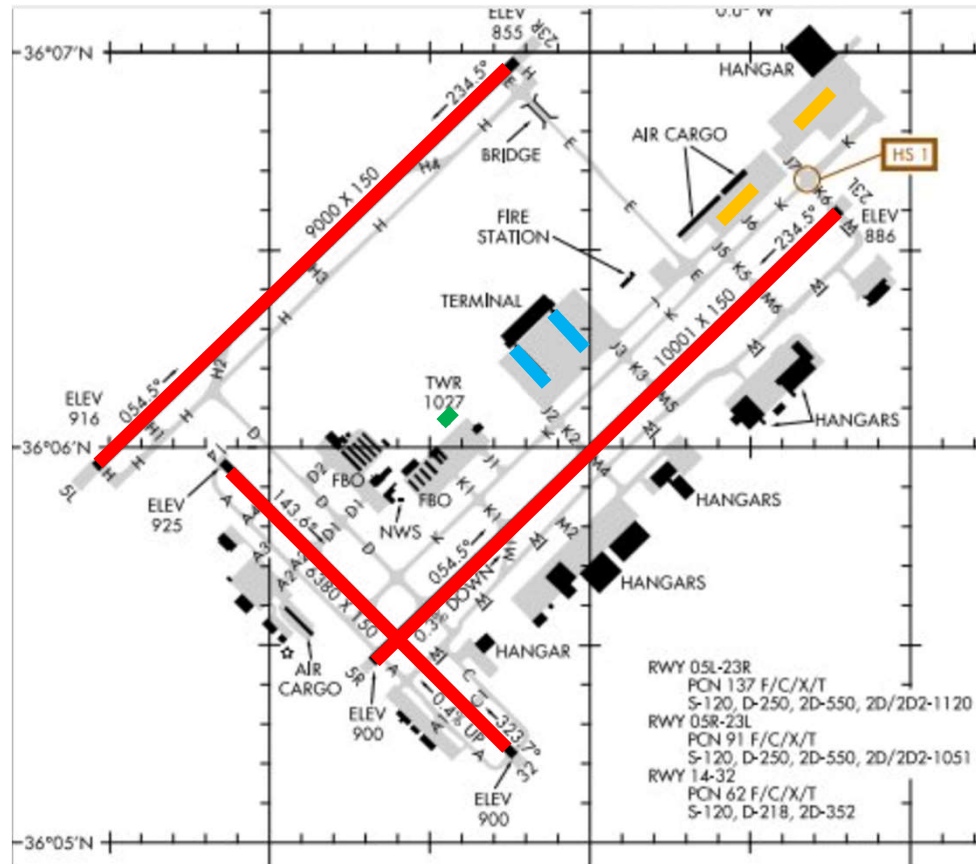
Proposed System Architecture



Digital Twin

- Use of classes to represent each object
- Prototype the environment
 - Detail of AP Lanes, ATC environment, tower location
- List of operations/events
 - Surface to air, Air to surface, Taxi, clearance
 - predictive suggestions, monitoring, airspace and traffic coordination
- Generates contextual data
 - From historical context of tower frequencies
 - Arrival/landing of aircrafts with different intervals (close to real events)
 - Wind, temperature, and forecasted weather data
 - With capability of getting inputs for simulation of an even of interest
- Provides actions that should be taken and considered

GSO Airport Layout



GSO Airport Photo



Aircraft Transponder

Destination

- Guided destination of incoming or taxing craft / vehicle

Position

- Current positioning of vehicles on way to and within GSO compound

Altitude

- Current positioning of craft in transit through air

Speed

- Current occurring speed of craft with regards to advised protocol

ETA

- Estimated Time of Arrival for aircraft approaching GSO compound

Tower Frequencies

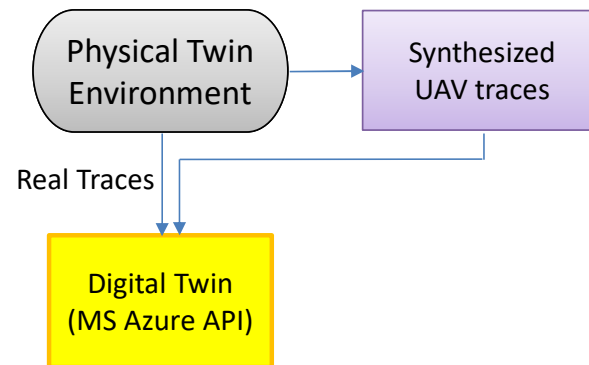
Used for communications with the tower and other airport services :

- ATIS (Automated Terminal Information Service): 128.55 MHz
 - Arrival/Departure
- Ground Control: 121.9 MHz
 - Ground Movement (Taxi, pushback)
- Tower: 119.1 MHz
 - Clearances for takeoff/Landing, Traffic advisories, Instructions for Aircraft in Vicinity
- Approach/Departure (A/D): 118.5 MHz
 - A/D within terminal airspace
- Clearance Delivery (CLD): 121.75 MHz
 - Clearance including routing and altitude
- UNICOM: 122.95 MHz
 - Pilot and ground coordination (fueling, maintenance)

Tower Frequencies (cont.)

Provides real data:

- Real traces of Events
- Possibility of artificial generation for UAV based on them



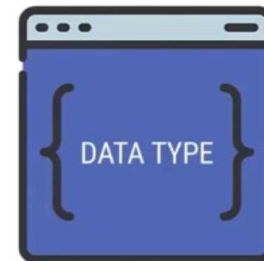
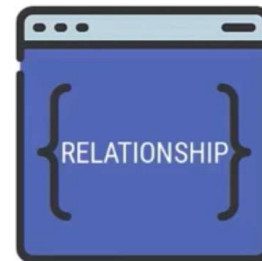
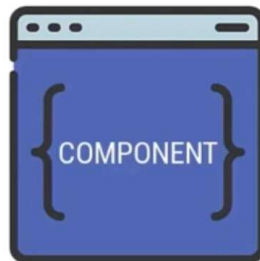
Microsoft Azure API

PROPERTY Metamodel Classes

Functions
performed by
physical entity
(Alter Speed)

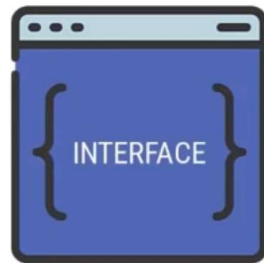


Components in
common
(Similar Sensor)



Microsoft Azure API

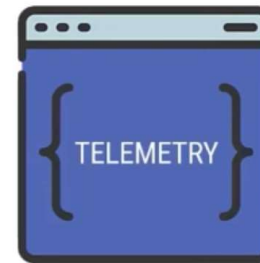
PROPERTY Metamodel Classes



Enclose all the elements within DT model

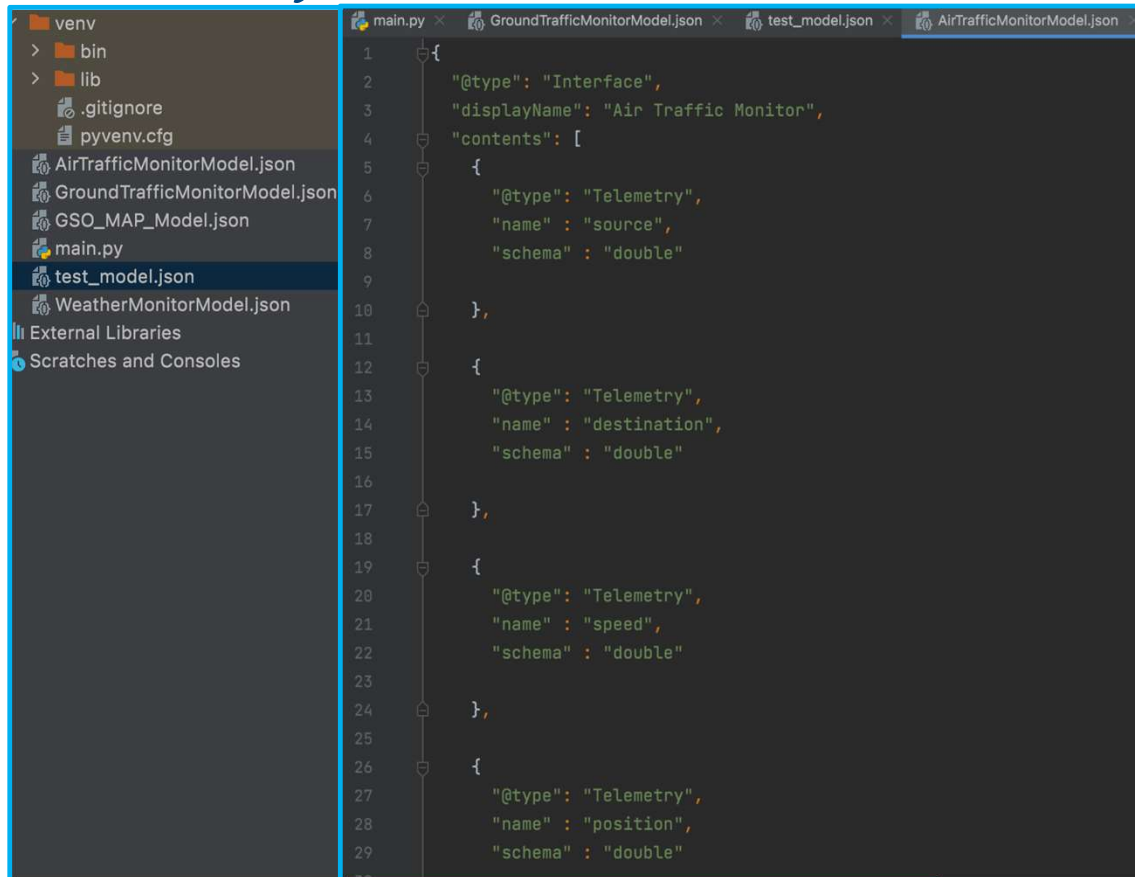


Elements that rarely change (Serial Number)



Data emitted by physical entity (Speed, Direction)

Microsoft Azure API (cont.)

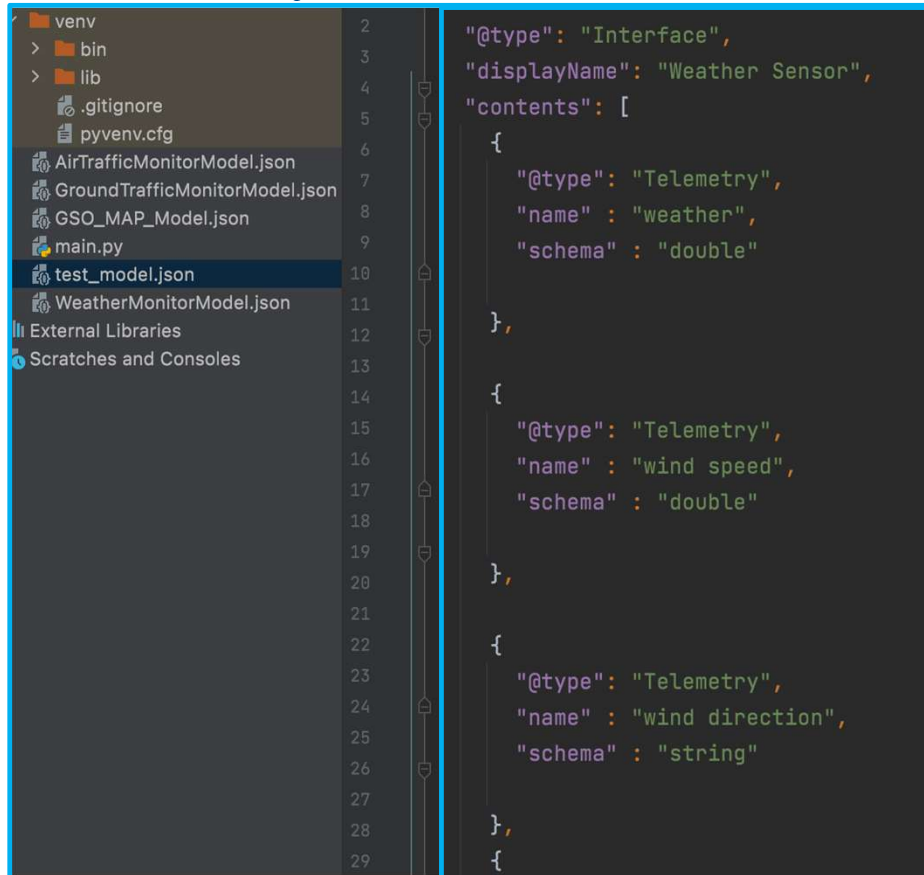


The screenshot displays a code editor with a project structure on the left and a JSON schema in the main editor. The project structure includes a `venv` directory with `bin` and `lib` subdirectories, a `.gitignore` file, a `pyvenv.cfg` file, and several JSON model files: `AirTrafficMonitorModel.json`, `GroundTrafficMonitorModel.json`, `GSO_MAP_Model.json`, `test_model.json`, and `WeatherMonitorModel.json`. The main editor shows the `AirTrafficMonitorModel.json` file, which defines an API interface with the following schema:

```
1 {
2   "@type": "Interface",
3   "displayName": "Air Traffic Monitor",
4   "contents": [
5     {
6       "@type": "Telemetry",
7       "name": "source",
8       "schema": "double"
9     },
10    {
11      "@type": "Telemetry",
12      "name": "destination",
13      "schema": "double"
14    },
15    {
16      "@type": "Telemetry",
17      "name": "speed",
18      "schema": "double"
19    },
20    {
21      "@type": "Telemetry",
22      "name": "position",
23      "schema": "double"
24    }
25  ]
26 }
```



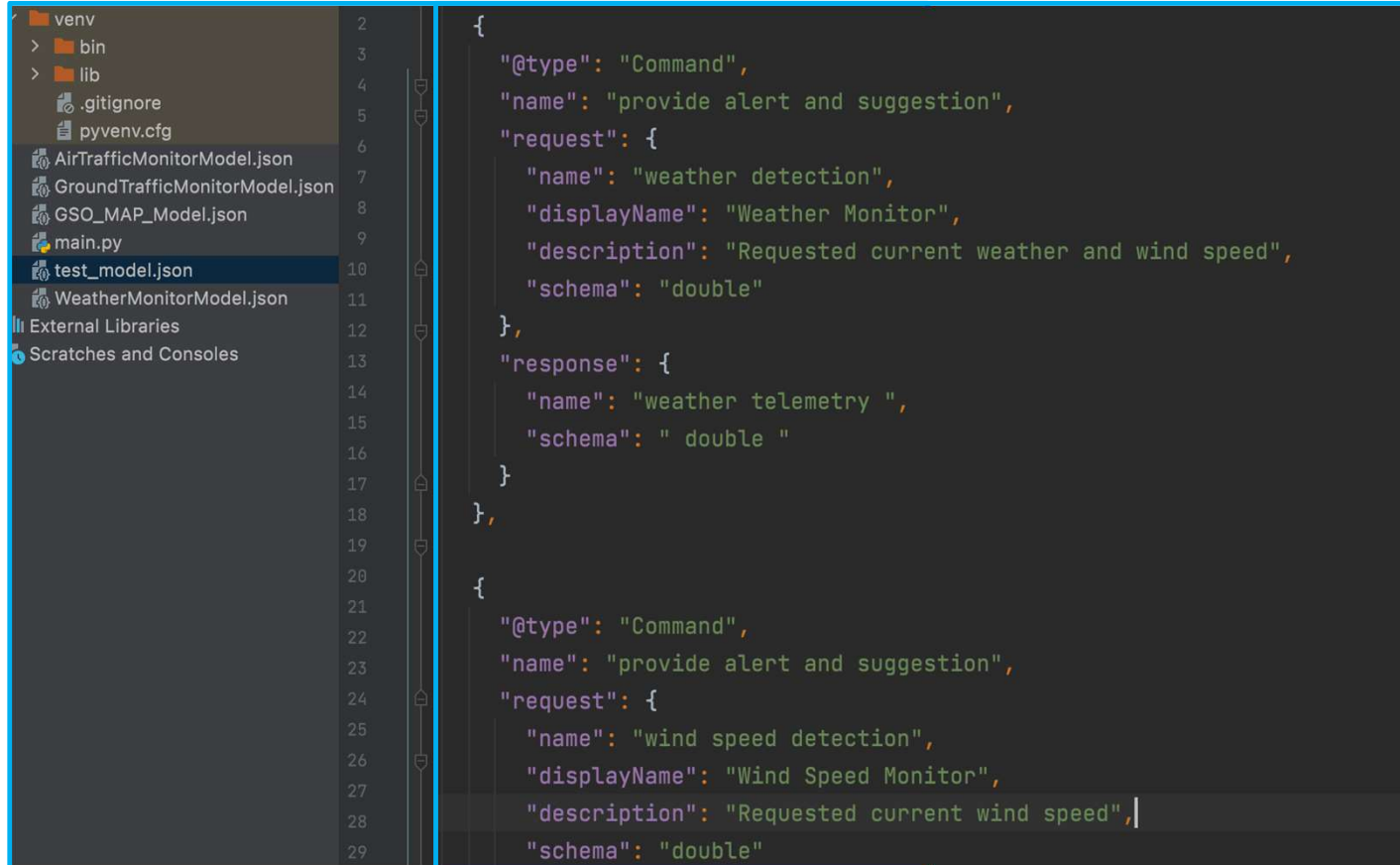
Microsoft Azure API (cont.)



```
2  {"@type": "Interface",
3
4  "displayName": "Weather Sensor",
5
6  "contents": [
7
8    {
9      "@type": "Telemetry",
10     "name" : "weather",
11     "schema" : "double"
12   },
13
14   {
15     "@type": "Telemetry",
16     "name" : "wind speed",
17     "schema" : "double"
18   },
19
20   {
21     "@type": "Telemetry",
22     "name" : "wind direction",
23     "schema" : "string"
24   }
25 ]
26 }
27
28
29
```



Microsoft Azure API (cont.)



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{
  "@type": "Command",
  "name": "provide alert and suggestion",
  "request": {
    "name": "weather detection",
    "displayName": "Weather Monitor",
    "description": "Requested current weather and wind speed",
    "schema": "double"
  },
  "response": {
    "name": "weather telemetry ",
    "schema": " double "
  }
},

{
  "@type": "Command",
  "name": "provide alert and suggestion",
  "request": {
    "name": "wind speed detection",
    "displayName": "Wind Speed Monitor",
    "description": "Requested current wind speed",
    "schema": "double"
```



Final Output: Traces with Decisions

Log:

Contextual Data/log 1

Contextual Data/log 2

Contextual Data/log 3

Change in Contextual Data/log 1

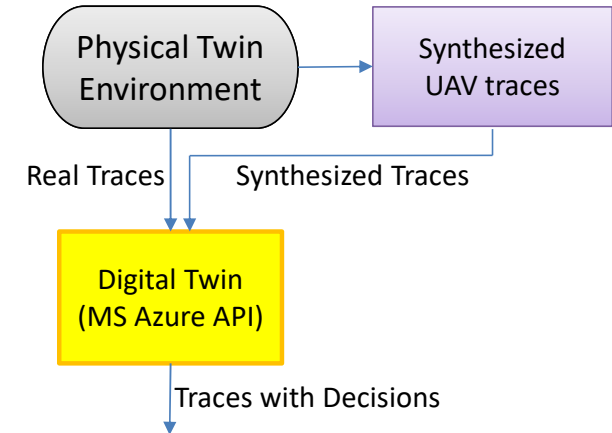
Event/Decisions by ATC “A”

Contextual Data/log 4

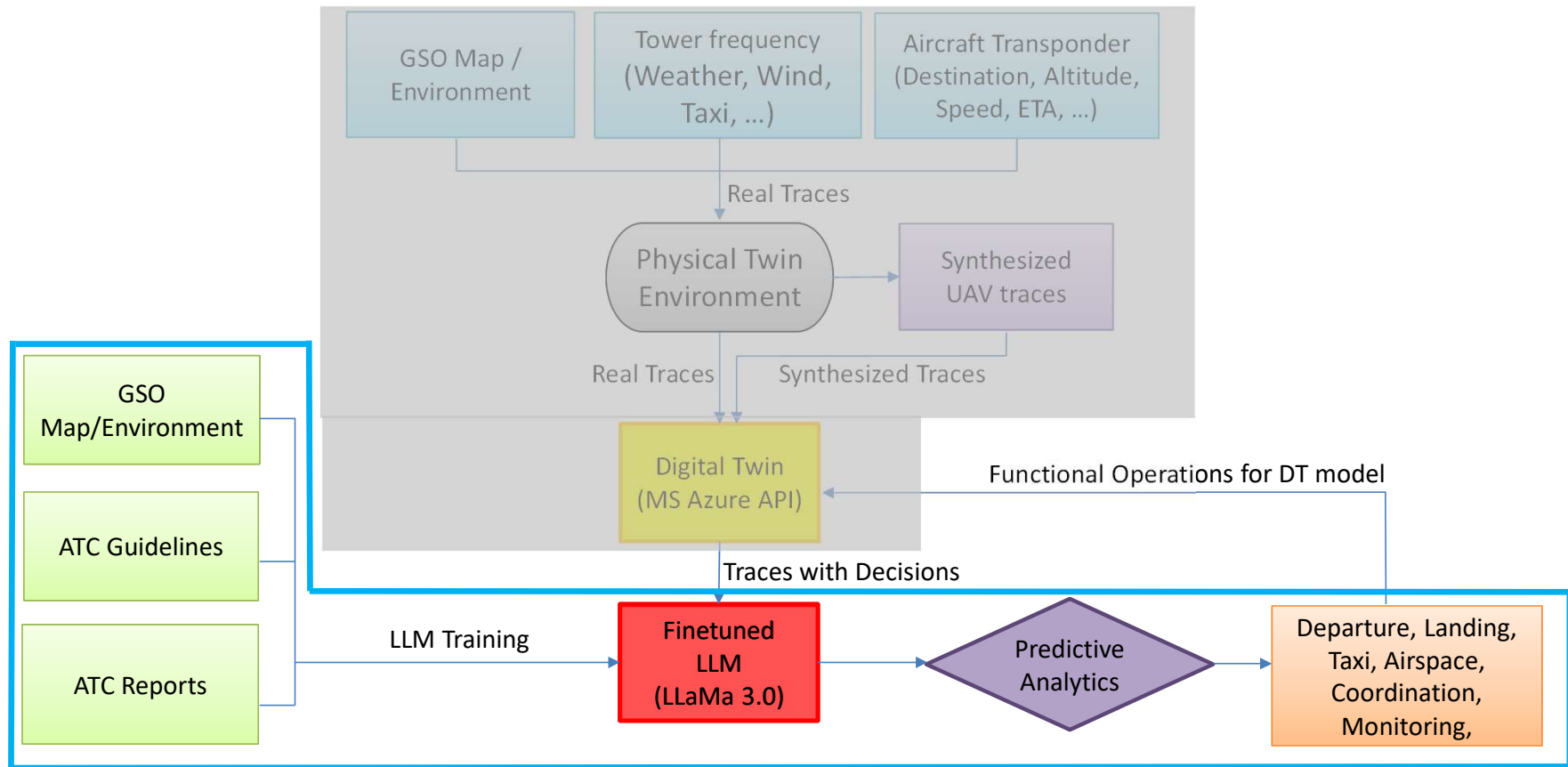
Contextual Data/log 5

Contextual Data/log 6

Event/Decisions by ATC “B”

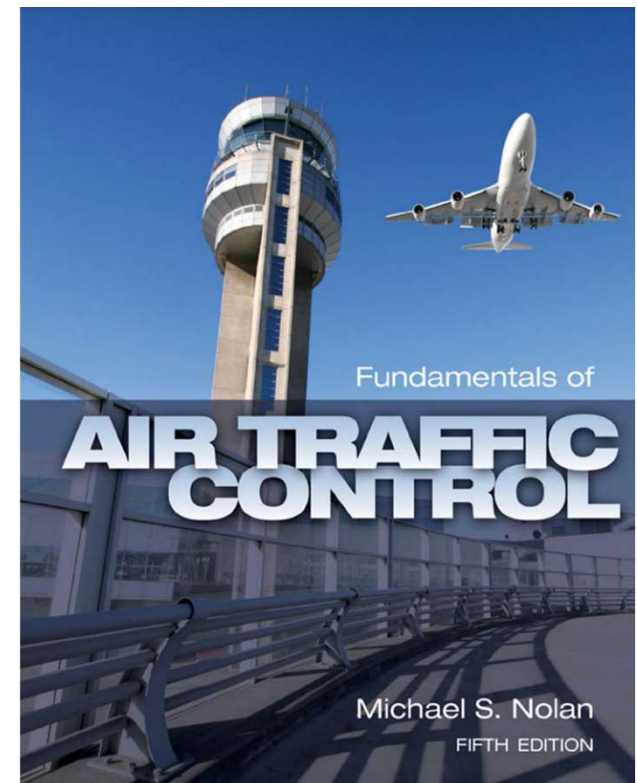


Proposed System Architecture



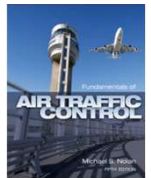
LLM for Predictive Suggestions

- ATC guideline book pretraining
 - GSO Masterplan for providing contextual protocol data



LLM for Predictive Suggestions

- ATC guideline book pretraining
 - GSO Masterplan for providing contextual protocol data
- Designing a model capable of understanding context
 - Using ASR dataset based on ATC narratives
 - Provide understanding of leading cause of issues
- Training on Digital Twin Data
 - Predicting future event/decisions



Predictive Analysis

New Log:

Contextual Data/log 12

Contextual Data/log 13

Contextual Data/log 14

Change in Contextual Data/log 14

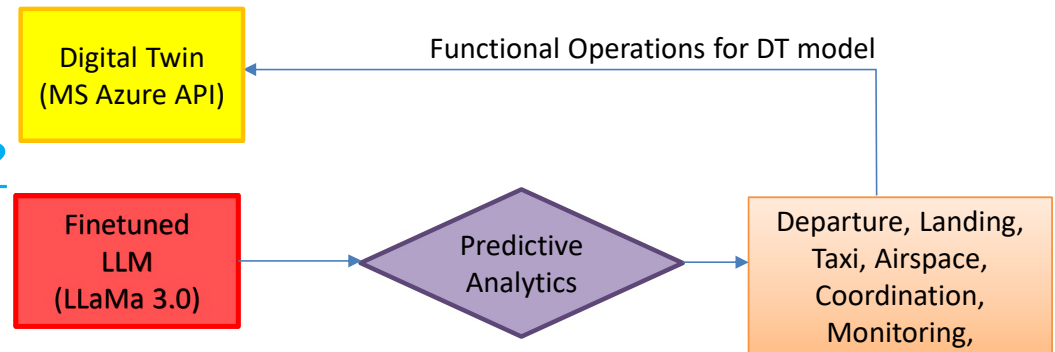
Event/Decisions by ATC "C"

Contextual Data/log 4

Contextual Data/log 5

Contextual Data/log 6

? Event/Decisions by ATC ?



Models & Training Methodologies

Models:

- Falcon
- LLaMA
- Vicuna

Training Methodologies:

- Fine Tuning & Prompt Engineering
- Parameter Efficient Fine Tuning (PEFT) techniques
 - Prefix-Tuning and LoRA based techniques [QLoRA/LongLoRA]



Proposed Timeline

Task 1:

- Development of Digital Twin
- Data generation for Model Training

Task 2:

- Autonomous Monitoring and Management
- Contextual Modeling for anomaly detection

Acknowledgment

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References

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Thank you!

