# END- TO -END AUTONOMOUS DRIVING USING REINFORCEMENT LEARNING TECHNIQUES

**By**

**Ola Akinkunmi**

**Abstract:**

Recently, Autonomous Driving has seen tremendous interest in both academia and the industry by curious and intelligent people from all over the world. As a species we have been dreaming of self-driving cars since we had the first automobile with an internal combustion engine by Carl Benz in (1886). This is because theoretically it looked easy to achieve self-driving automobiles because it was simply grouped into sensory data and vehicle control commands (accelerate, break and steer). The idea was quickly rebuffed, and the magnitude of the problem was understood to be more complicated, complex and inverse from the Computer Network Engineering and Internet Search viewpoint given the dynamic environment of the road network with cooperative and non-corporative games happening among multiple participants/players. Promising trials of self-driving cars took place in the 1950s right around the birth of Artificial Intelligence in 1956, with notable autonomous driving milestones in the 1980's.

End-to-End autonomous driving approaches consist of three different Architectures:

**a)** Modular Approach

**b)** The Hybrid Model, which is sub-divided into 2 paradigms.

- Mediated Perception
- Behavior reflex/Immitation learning

**c)** End-to-End Algorithm, which consists of two paradigms.

- Direct Perception
- Reinforcement Learning

Modern research and growth are focused on Direct Perception and Reinforcement learning but I would cover the Rule-Based-Algorithm/Modular approach introduction to serve as a pivoted point into the future of Autonomous Driving using reinforcement learning.

Before I discuss each of the approaches in a bit more detail, the figure below shows the architecture overview of each approach to autonomous driving.

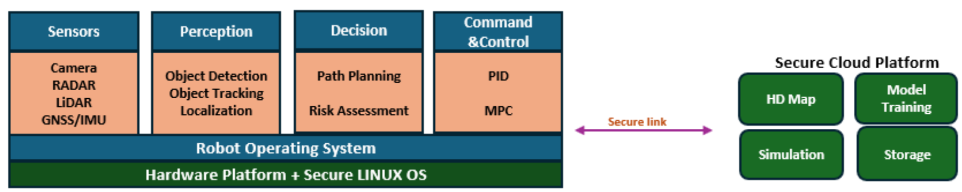


**FIGURE A: SHOWS THE MODULAR ARCHITECTURE OF INTERCONNECTED MODULES AND SUBORINATE FUNCTIONS.**

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## SECTION 1

### Introduction

Autonomous Driving System is a complex system that integrates multiple technologies from Sensors/hardware, Central Processing Units, Storage, Software, Networking, Artificial Intelligence, Cybersecurity etc. Therefore, it should be able to deal with and recover from a wide range of problems such as sensor inaccuracy/malfunction, hardware/networking reliability, covariate shift, cybersecurity attacks etc.

Currently, the classical method which is widely used in the industry to achieve Autonomous Driving results is through the **Modular Approach**, whereby the driving task is divided into respective tasks/modules such as localization, object tracking, path planning, obstacle avoidance etc. and then these individual modules are connected using rule-based designs to get a whole system.

**The Modular approach** enjoys the benefit of a matured industry framework to connect different modules of the AD system such as Robot Operating System (ROS) which allows for independent development and optimization of each task/module by various specialized engineering teams. The obvious disadvantage is integration complexity and since each module is specialized it will fail to generalize about unexpected situations or unfamiliar conditions. This popular quote explains it better: "Jack of all Trades (60%-80%), is a master of none though oftentimes better than the master of one."

Another advantage of the **Modular approach** is the interpretability, since the system is divided into modules, a source of malfunction can be tracked to the module responsible for failure. Error Propagation is the disadvantage of this approach because a mistake in one module, such as inaccurate object detection in perception can impact subsequent modules potentially reducing system reliability or result in a catastrophic accident e.g. Misclassification of traffic light can impact the path planning task and decision-making module which can lead to a collision or accident.

**The Mediated Perception approach** involves using multiple sub-components for recognizing objects relevant for Autonomous Driving and these are technically called "Avoidances". They include traffic lights, lanes, distance to the center line, traffic signs, pedestrians, distance to vehicles etc. The computer vision recognition result of the "Avoidances" is then parsed and combined into a consistent world view of the car's immediate surrounding. For vehicle control, reinforcement learning will then take this environmental information to make predictions and decisions.

An advantage of using **Mediated Perception** is that we are infusing human knowledge into the system, instead of expecting the AI system to learn all relevant information from scratch. The disadvantage with this method is only a small portion of the objects detected are relevant to driving decisions, so a total scene understanding adds unnecessary complexity to an already difficult task e.g. Avoidances like fences and walls would be redundant information in most use-case. Another example is the detection of a bounding box of a car and then use the bounding box to estimate distance, when we can simply predict the distance to the car directly.

In addition to the advantages and disadvantages mentioned, earlier **Mediated Perception** shares the same advantages and disadvantages with Modular Approach Architecture mentioned earlier.

**Behavioral Reflex** is a supervised learning approach that dates to the late 1980's in which the neural network model tries to mimic human behavior without the hard-coded reward design. To teach the model, a human drives the car on the road or in a car racing simulation video game such as Grand Turismo Sports/7 or future versions, while the system records the images and steering angles as training data.

The benefit of using **Behavior Reflex** is simplicity which means it is easy to copy surface level actions and implement. The drawback to this approach is the copycat problem or casual confusion, where the model relies on wrong correlations between certain input components and output response for example, if there is a leading car, one may decide to follow the car, overtake from the left, or from the right. But when all these scenarios exist in the training data or none exist, a neural network model will have difficulty deciding what to do given almost the same images or no similar image of the scenario.

Another benefit of **Behavior Reflex** is elegance and efficiency which allows the ego vehicle to react instinctively to various driving scenarios without complex-decision making processes. The downside is the direct mapping/behavior reflex cannot see the bigger picture as the decision-making ability is too low for the situation. E.g. From the neural network perspective, a multiple lane road and a single road where overtaking is permitted can be viewed as the same. Though similar, as they both have broken lines marking, misclassifying them together can lead to catastrophic accidents or ending.

**Direct Perception approach** directly predicts the affordances for Autonomous Driving, instead of inefficiently parsing the entire scene or blindly mapping an image to steering angles, Direct Perception approach learns a mapping from an image to several meaningful affordances which includes road signs, lane marking, angle of the car relative to the road etc. This is optimized towards the ultimate task of a safe and smooth autonomous driving car where the low-level controller can now make driving decisions at a high level.

**Direct Perception Approach** uses a Deep Convolutional Neural Network **(DCNN)** framework to dynamically learn image features for estimating avoidances related to Autonomous Driving in combination with Deep Q Network **(DQN).** The training data for the Deep Convolutional Neural Network is gotten from recording screenshots and corresponding labels from a physical human driver or a human driver playing a simulation car racing video game with a controller for about 16 hours. Example of such games include Grand Turismo Sports/7 or future versions.

**Reinforcement Learning** involves modelling behavioral psychology used in training the human brain. Its application in Autonomous Driving is quite recent with the first version in 2016, and the next three years focused on simplifying and optimizing the original version e.g. lane changing, lane following etc. It is a method of learning through trial and error as it utilizes Deep Q network **(DQN) or** Deep Deterministic Policy Gradient **(DDPG)** to maximize the cumulative rewards received by an intelligent system as it interacts with the environment.

DQN works by training a neural network called “Critic or Q network” which takes the current state of an action as input and predicts the discounted feature reward of that action. The policy is then implicitly defined by selecting the action with the highest Q value when following the same policy afterward.

**Reinforcement Learning** downside at the training stage is it requires an environment that allows potentially unsafe actions to be performed since it utilizes exploration, which might result in execution of some random actions during data collection. To meet this requirement in real-world cars, present

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great challenges, therefore most papers that incorporate Reinforcement Learning in autonomous Driving have done the techniques in close-loop simulation software such as Grand Turismo, AirSim, Carla, etc. But it should be noted that open-loop versions exist such as Apollo, Mobileeye, Waymo etc.

**Reinforcement Learning** is also more data hungry during the training period than the Supervised Learning method in the Direct Perception approach, but they ultimately get to the same goal.

## SECTION II.

## Discussion.

This section is about understanding the architecture design of the modular approach. The Carla implementation model has been completed and submitted. It utilizes Camera and Lidar for the sensor.

### ARCHITECTURE:

Here, I will be discussing the overarching modules and their subordinate functions for the modular approach. The modules are Sensor, Perception, Decision Making and Command and Control

#### a) SENSORS

The subordinate functions are the physical eyes and ears of an AV system. They convert sensed events and/or environmental changes into a numerical measurement to identify objects, enable localization etc. This is after processing is done internally and in a point cloud (RADAR and LiDAR). Sensors are classified based on functional principles into two major types which are **Proprioceptive sensors/Exteroceptive** and **Passive/Active.**

**Proprioceptive sensors** are electronic devices that measure data and values internal to the AV system. E.g. motor speed, wheel load, battery voltage, Inertial Measurement Units (accelerometer, gyroscope, magnetometer)

**Exteroceptive sensors** acquire information from the AV's external environment such as distance measurement, sound amplitude, light intensity. Examples include Cameras, Ultrasonic, GPS receivers, Radio Detection and Range (RADAR), Light Detection and Range (LiDAR)

**Passive Sensors** receive and measure environmental energy entering the sensor e.g. microphones, temperature probes, Cameras, GPS Receivers.

**Active Sensors** emit energy into the environment and measure the reaction. They typically achieve superior performance because they manage a more controlled interaction with the environment, but the risk is that outbound energy may affect the very characteristic that the sensor is trying to measure. Active sensors include Ultrasonic, Radar, Lidar.

### SENSORS SUBORDINATE FUNCTIONS

Sensors in Autonomous vehicles typically use a multimodal approach, integrating various data sources such as visual inputs from camera, spatial/wireless technology mechanism (Ultrasonic, RADAR, LiDAR) and auditory data from microphones to enable the vehicle to make more informed and accurate decisions. I would highlight and summarize Autonomous Vehicles sensors from the **External/Exteroceptive** perspective.

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**CAMERAS**: I See. This can be grouped into **Monoscopic** and **Stereoscopic**. It is a critical and popular component of autonomous driving because they are relatively inexpensive and have high-resolution capabilities. It works by detecting light emitted from the surroundings on a photosensitive surface. Limitations of cameras include difficulty identifying objects at long distances, lack of proper visibility in low-light conditions etc.

**Monoscopic** cameras capture a single image from one viewpoint/flat 2D view. This imitates what a single human eye would see. It lacks perception in-depth and is simpler to set up and use. It is commonly used for standard photography or most CCTV cameras.

**Stereoscopic** cameras are used in autonomous driving for realistic 3D experience. They capture two images from slightly different angles mimicking the human eye's perspective. It provides a sense of depth while also requiring more precise alignment and post-processing to create the 3D effect.

**RADAR:** And the winner is Air and Intelligent Transportation. Using Electromagnetic waves It is used for contactless detection, positioning of objects, speed and location tracking etc. It is also called active transmission because it emits Microwaves which is a subset of radio waves which bounces off objects in its path and the sensor receives the reflected signal. Radars are independent from heat/cold weather conditions, it works in bad or no lightening conditions and is not visible with human eyes. On the flip side of things RADAR have a lower resolution than lidar or camera making it difficult to identify small objects or distinguish between similar objects. It is also subject to interference by other RADAR systems which reduces its accuracy.

**LiDAR**: Let there be light. Its operating principle is like RADAR but uses infrared laser light which is not visible to the naked eye to measure distances between objects after emitting light pulses on the object. There are multiple types of lidar technologies used for various functions such as **Airborne lidar** mounted on drones and helicopters, **Terrestrial lidar** on the ground which can be *static* or *mobile*, **Bathymetric** which uses green light to measure seafloor and riverbed elevations, **Wind Lidar** to measure windspeed, turbulence and direction, **Spaceborne lidar** for global mapping, environmental studies and climate monitoring.

In **autonomous driving**, the common Lidar types include Time of Flight Lidar, Flash Lidar, Scanning Lidar, Frequency-Modulated Continuous Wave. With each having its own positives and negatives. Various types can also be combined to achieve a certain performance and/or reliability base on use case. Finally, Lidar is very important to AV as the remote sensing technology is very accurate and not dependent on weather and light conditions. The downside is its data is not colorized, making it difficult to interpret without an overlaying RGB photo.

**GNSS Receiver:** Riding the waves to Space. This is a critical component in autonomous driving. GPS was originally developed by the US Department of Defense for use by the US Military during the cold war. It relies on a network of satellites which orbit the earth and transmits signals using microwaves that allow a GPS receiver to determine its exact position, speed, course, longitude and latitude using a process known as satellite triangulation. It also works with other sensory technologies to provide localization for the autonomous vehicle.

Drawbacks of GPS include **signal obtrusion and interference** in urban areas, tunnels and densely forested areas. Another Issue is **Weather conditions** such as snow, dense fog, rain etc. can degrade the signal quality leading to discrepancy in positioning data. Finally, **GPS signal spoofing and jamming** remains a big concern; _Spoofing_ is the broadcast of malicious and/or fake GPS signals which can mislead an autonomous driving navigation system. _Jamming_ on the other hand is a denial-of-service (DOS)/distributed denial-of-service (DDOS) attack whereby legitimate GPS frequency and/or data is prevented from reaching the intended host resulting in loss of signal integrity.

To mitigate these vulnerabilities, it is important to have redundancy in the navigation system, multifrequency and multi constellation etc. Integration of Inertial Navigation System (INS) to support GPS data to "centimeter level accuracy" is also being used. Finally, other cybersecurity techniques such as cryptography, direction-of-arrival-sensing, signal distortion detection etc. should also be used as best practices.

**Ultrasonic**: The Miracle of Sound. Ultrasonic operates under the "echolocation principle" which Bats use to find their prey. Like RADAR and LiDAR, it emits a high pitch sound that bounces off objects and measures the distance in between. This is usually between 23KHz and 40KHz, while human hearing audible range is 20KHz. This is also a popular technology in the autonomous driving industry.

Advantages of ultrasonic include it is unaffected by the color of the object being detected including translucent or transparent objects such as water or glass. It is a mature technology, inexpensive with precise and accurate measurement. Ultrasonic is also resistant to electromagnetic interference (EMI) and acoustic noise, especially when equipped with encoded chips.

Downsides include environmental conditions such as temperature and humidity can change the speed of sound therefore reducing the precision of the measurement. It cannot provide feedback on any of the features measured such as color or shape as it only detects there is an object within range.

### b) PERCEPTION

The Perception module in an Autonomous Vehicle is very important because it gathers and processes data from multiple sensors attached to enable the vehicle to recognize and understand the avoidances and other elements in the surrounding. The subordinate functions for the perception module include object detection, object tracking and localization.

### PERCEPTION SUBORDINATE FUNCTIONS

**Object Detection:** I will find you. This is a key aspect in Autonomous Vehicles as it allows the ego vehicle to locate and identify objects by combining deep learning models and computer vision to analyze and interpret data from various exteroceptive sensors to navigate the road efficiently and securely using Deep Convolution Neural Networks (DCNN).

DCNN helps AV see by processing sensor data. It examines one or a combination of images/videos, 3D Lidar data etc. for vital cues such as edges that would be used for object recognition and identifying what makes them unique. Once the object has been classified, they are matched with their proper labels. Fully connected layers and SoftMax functions weigh the chances of an object fitting a certain class to speed up the decision-making process. It should be noted that DCNN uses **adaptive detection** to differentiate avoidances, which is better than the traditional model because it improves safety, enhances reliability and reduces false positives. It can also continuously learn and adjust its parameters to handle variations in input data and improve performance in diverse scenarios.

**Object Tracking:** I am monitoring you**.** This is another critical component of Autonomous Driving that helps the ego vehicle perceive its environment to ensure a safe and robust driving experience. It uses the 'object detection algorithm output' as an input to the 'object tracking algorithm' to estimate and predict the positions and/or other relevant information of moving objects in a video despite any occlusions. It is divided into four different types namely Image/video tracking, Single Object Tracking (SOT), Multiple Object Tracking (MOT), Point Cloud and Multimodal Fusion Based Object Tracking.

*Image/Video Tracking* detects and locates objects in photos/video inputs (live or recorded). In photos, the targeted object is detected, identified and stored which can then be used to identify the same object in other photos. For video, the specified image tracking is applied to each frame after the video has been divided into multiple frames.

*Single Object Tracking (SOT)* focuses on tracking a single object of interest within a scene allowing the autonomous car to predict the movement and make informed decisions for safe navigations. Its application is more geared towards sport analysis or medical imaging. It utilizes either video frames from a camera or 3D lidar data, but the latter is considered essential for AV safety.

*Multiple Object Tracking (MOT)* is like SOT but handles and tracks the movement of multiple objects within a video simultaneously. Commonly used in surveillance systems, crowd analysis and autonomous driving. It is more complex as it must identify and distinguish multiple objects. MOT must solve two additional tasks for autonomous driving which are: **i)** determining the number of objects **ii)** maintaining their identities. It can also serve as a pivot point for other non-driving related tasks such as facial recognition, emotion detection, behavioral analysis, pose estimation, action recognition etc.

*Point Cloud and Multimodal Fusion Based Object Tracking* This is the current development trend for object tracking that aims to integrate multiple data sources for object tracking such as camera, Radar, Lidar etc. The results have been promising and effective in tracking objects. It would later be part of SOT and MOT object tracking once maturity is reached.

**Localization:** I know where you are**.** It is used to determine the precise location and orientation of an autonomous vehicle within an environment using GNSS in combination with one or many other sensors such as Camera, Radar, Lidar, Inertia sensor, IMU etc. Unlike the use of GPS on navigation maps that require an accuracy of a few meters, localization requires absolute reliability together with accuracy in the order of centimeters or a few tenths of a degree.

It is very important in autonomous driving because it orients the vehicle to the unique feature of the road such as lane marking and guard-rails. It also allows the vehicle to make high level decisions beyond its current field of view e.g. detecting a lane merge, plan lane change etc. Finally, it gives the ego vehicle the ability to understand other driving participants/players e.g. understanding that a car upfront is in a left turn lane and would not proceed straight.

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### c) DECISION-MAKING

This is referred to as the brain of the Autonomous Driving as it acts as a bridge between the perception and the control command modules. The decision-making level determines the safety, comfort, efficiency and energy consumption of the autonomous vehicle which directly affects the passengers in it. There are two ways to design the Decision-Making module which are Rule-based approach and Reinforcement learning approach.

**Rule-based behavior decision model** approaches are relatively simple, have strong logic and are easy to modify, but fall short when the scene environment becomes complex. It is widely used in the current behavior decision-making subsystem of autonomous vehicles.

**Reinforcement Learning** involves utilizing Deep Q Network (DQN) or Deep Deterministic Policy Gradient **(DDPG)** for the decision-making module of the autonomous vehicle. One major key-takeaway is by utilizing this method, the approach shifts right to a **Hybrid End-to-End approach (Mediated Perception).** Kindly refer to page 2 for more details on Mediated Perception and page 4 for more details of reinforcement learning.

### DECISION-MAKING SUBORDINATE FUNCTIONS

**Path-Planning:** Network Engineering and Internet Search. This subordinate function is very important and equally a hard problem to solve. It aims at providing a safe trajectory for the ego vehicle using two phases. Firstly, a global and optimal route is generated from the origin to the destination based on GNSS localization and an online/offline map. The final step is to get an obstacle-free local path that executes the global path without collision. This function is divided into three major types. Traditional, Optimization and Reinforcement Learning Approach.

*Traditional path planning*: This is an ongoing research area with multiple variations to solve the Non-Deterministic Polynomial Time (**NP-hard)** problem which is to find the shortest and optimal path without exponentially increasing the number of available nodes/costs. E.g. Routing protocols, maps, search engines. Cryptography on the other hand is based on the NP-hard problem but aims to increase the polynomial Time required to solve the NP-hard problem. There are multiple methods, variations and combinations being explored to solve the NP-Hard problem that's beyond this scope but here are a few individual ones. ***Graph Based Method***- Dijkstra Algorithm, A* Algorithm ***Sampling Based Method***- Kinematic Constrained Bi-directional Rapidly-Exploring Random Tree (KB-RRT), SPRINT Algorithm, Line Segment Algorithm etc.

***Gradient Based Method***- A hybrid of Improved Artificial Potential Field (IAPF) and Gradient Descent Method (GDM)algorithm (IAPF-GDM), Adaptive Potential Field for Path Planning (ADPF-PP) Algorithm.

*Optimization path planning*: This attempts to use numerical solutions to optimization problem. It is known as convex programming whereby the objective function is minimized, and concave programming when the objective function is maximized. Examples of optimization **NP-Hard** problem are the 'Advanced Driver Assisted System' that tries to solve the convex/minimization problem. Network optimization, search engines etc. are other examples. Optimization-based algorithms include:

Genetic Algorithm-Potential Field (GA-PF), Simulated Annealing (SA), Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO) algorithm, Artificial Bee Colony (ABC) algorithm, Beetle

Antennae Search (BAS) algorithm, Firefly Algorithm (FA), Chicken Swarm Optimization (CSO) algorithm, Cat Swarm Optimization Algorithm (CSOA), Cuckoo Search Algorithm (CSA), Teaching-Learning-Based Optimization (TLBO) algorithm,

*Reinforcement Learning path planning*: Involves utilizing Deep Q Network (DQN) or Deep Deterministic Policy Gradient **(DDPG)** for the path planning subordinate function. Kindly refer to page 4 for more details of reinforcement learning.

**Risk Assessment:** Import Surface Cybersecurity. This subordinate function is very vital and responsible for the overall risk estimation and predicting the actions and inactions of the drivers and road participants to prevent an accident. It undertakes three major tasks which are **i)** Identifying the driving style, **ii)** assessing the behavior of the surrounding human drivers and road participants **iii)** conducting uncertainty and risk assessment.

*Identifying the driving style*: This is the most common task in the assessment. It is identifying the human driver's style from aggressiveness, normal, conservativeness and surrounding vehicle's relative speed. It uses unsupervised learning algorithms such as PCA algorithm, K-means clustering etc. and unsupervised learning methods such as neural network (Which mimics the human brain functionality), SVM to classify the driving styles.

*Assessing the behavior of the surrounding human drivers and road participants*: This involves understanding the intentions of surrounding drivers and road participants by predicting the behavior to avoid accidents e.g. predicting overtaking behaviors, lane changes and dangerous cuts performed by drivers and road players. The issue here is the short time-line available to sense the road players and surrounding vehicles in real time which needs to be improved to predict long term behavior.

*Conducting uncertainty and risk assessment:* This involves monitoring the overall driving scene to detect changes on the road such as obstacles and unsafe driving behaviors and conduct. It relies on the exteroceptive sensors and detection algorithm.

### d) CONTROL COMMAND

This is the final step of the sequence. Generating an angle for steering wheel and acceleration. Basically, in charge of moving the vehicle. It uses a controller whose sole purpose is to generate instructions for the vehicle such as steering wheel angle or acceleration level considering the actual constraint (road, weather, obstacles, etc.)

There are various implementations of the controller with the simplest and most common of all called **Proportional Integral Derivative** (PID). I will be discussing Model Predictive Control (MPC).

**Model Predictive Control:** God's hand and feet. This considers the forces that apply to a vehicle, characteristics, etc. It is more difficult to implement but also more effective. It uses actuators which basically moves the vehicle. An ego vehicle has three types of actuators namely steering wheel, accelerator and Brake Pedal. A MPC plays on these actuators by moving the steering angles and add/subtract pressure on the accelerator or brake pedal.

The MPC optimization algorithm calculates several pairs (angle, acceleration) and chooses the one with the lowest error and cost. MPC controllers are very powerful but also very difficult to implement, allowing the vehicle to reach faster speed while being safe.

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## CONCLUSION

In this paper I have been able to show the current evolution of autonomous vehicles from the modular approach to the end-end- algorithm. I focused this assessment on the modular approach which is the current version commonly used by vehicle vendors to bring an understanding into this nascent industry but has its limitations which is what the end-to-end approach aims to solve. The practical implementation which I would share is on the modular approach with further research focused on the end-to-end direction. I am glad to be at the beginning of my 4th level in researching Energy in Motion line from **Electrical** -> **Network** -> **swimming/running-> Transportation engineering** ∞▌☯

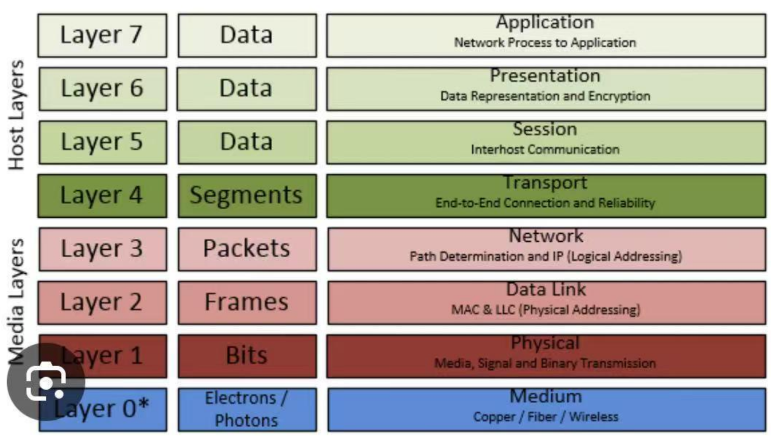


FIGURE 2: **SHOWS THE OSI LAYER FOR NETWORK ENGINEERING**

This shows the interconnection between Electricity, Network and Transportation. Which is all Energy/Celestial body motion

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