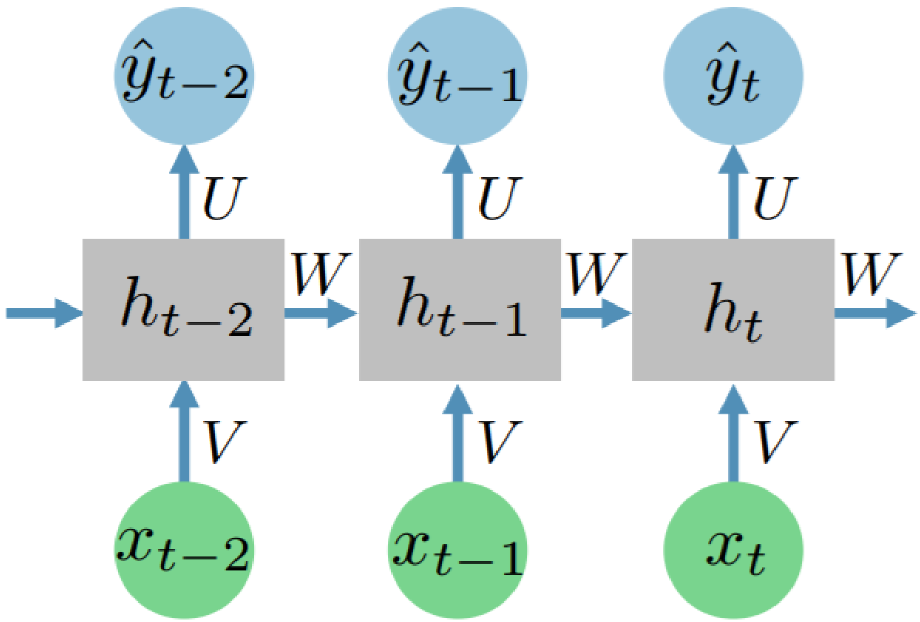
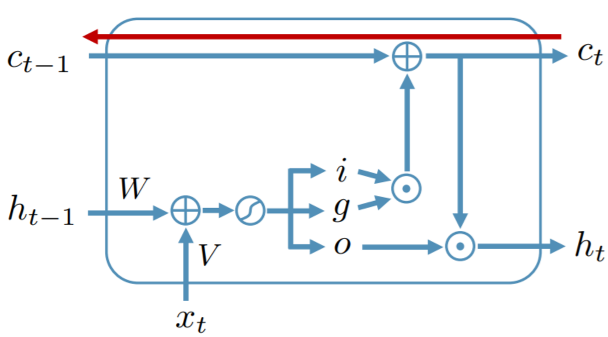
Recurrent Neural Networks:



A **recurrent neural network** (**RNN**) is a class of Artificial Neural Networks. Recurrent neural networks were based on David Rumelhart's work in 1986. In this Architecture, We work with a sequence word by word. So we see only one word in one time step.
Here our MLP has not only one output that transfers to the next layer, but also the second output that transfers to the next time step. Therefore, Now it's not necessary for our MLP to use all of the previous words as an input at the same time. It's enough to take only one current world, but also to take its own second additional output from the previous time step. As a result, our MLP now has a fixed number of parameters.

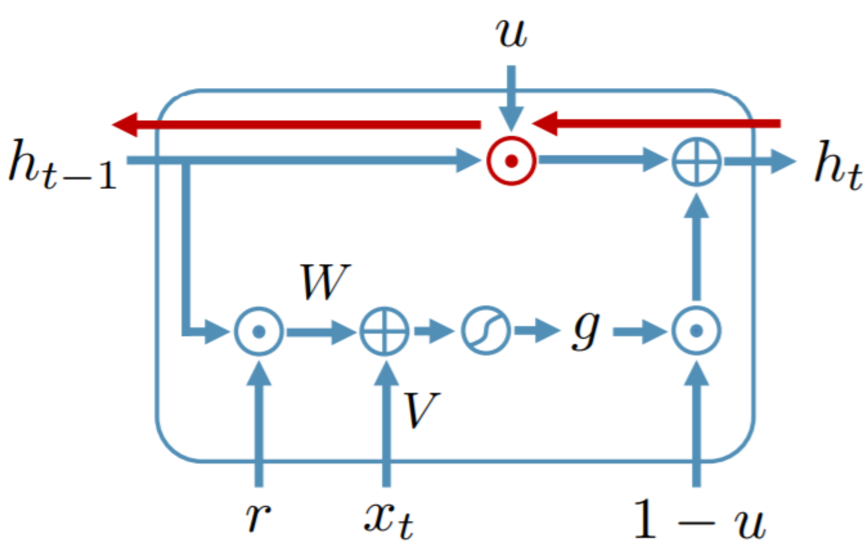
LSTM:



In the LSTM Layer, At each time step, we compute not only the vector of hidden units but also a vector of memory cell c on the same dimension and as a result, we have two ways through such layer, one between hidden units and the second one between memory cells. The input gate controls what to store in the memory. The information Vector g is multiplied by input gate and then added to the memory.

LSTM has more advantages than simple RNN but it has four times more parameters because each gate and the information left in g has its own set of parameters v,w, and b. This makes LSTM less efficient in terms of memory and time and also makes the GRU architecture more likely.

GRU:



Gated recurrent architectures: LSTM and GRU. They do not suffer from vanishing gradients that much because there is an additional short way for the gradients through them.

Recurrent Neural Networks, LSTM, GRU for Autonomous Vehicles:

Once upon a time cars were driven by the pure will and sweat of decent humans. Today technology has reached the point in which complex systems can drive the car with little or no human interaction at all. Autonomous driving is a field of research directed towards creating vehicles that will maneuver along roads towards a set destination while obeying traffic rules and avoiding unwanted collisions. The idea of removing the human from control has a multitude of reasons often around comfort, however, a more hands-on reason is driving safety. Removing the human factor would be a strong step towards improved safety for driving in motor vehicles. Another opportunity would be the ability to optimize traffic flow by allowing the vehicles to communicate their speed and trajectories to each other and calculate an optimal plan of action.

The main part of Autonomous driving Vehicles is Object Detection. This can be achieved by Recurrent Neural Networks. Semantic and Instance segmentation is also done by Recurrent Neural Networks.

By using the LSTM model we can design an autonomous driving policy model. In the problem of trajectory prediction, the future prediction is usually based on past experience or the history of previous trajectories. Thus, LSTMs, designed to process time sequence data, can likely perform well on such a task. Alahi et al. proposed a novel LSTM model in predicting human trajectories in the crowded space and Xue et al. incorporated more information including occupancy map and camera image to build a robust model in predicting pedestrian trajectories. Such ideas are also effective in predicting cars' trajectories as cars and pedestrians share common motion patterns to some degree. Inspired by their work, we will consider using LSTM-based approaches to process the time series data in the Waymo dataset and learn the driving policy underlying it. In addition, a non-LSTM-based method can be effective among the trajectory prediction problems. Martorelli has introduced a non-LSTM-based method using a Fuzzy controller to predict trajectory for nonholonomic wheeled mobile robots.