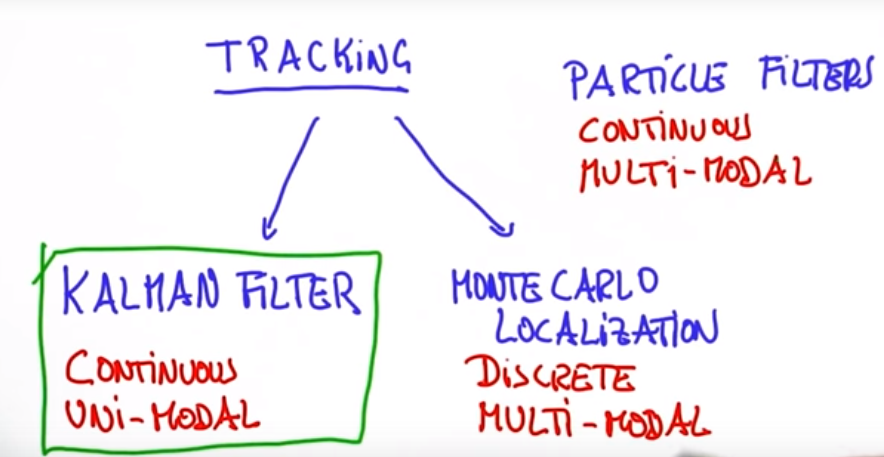
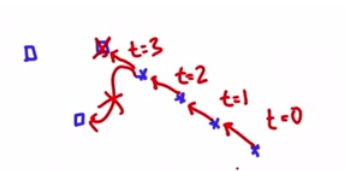
**Kalman Filters**

LIDAR gets distance measurements 10 times a second of about 1 million data points. This large amount of data is required to accurately place objects and your environment.

Gaining Data about where vehicles currently are is important for localization. It gets us information of other objects are so that there is no collision. However we also need to know how fast they are moving. That way we can use this information to predict where cars are going to be, in order to avoid collisions and hazardous situations. It’s important for all objects, whether it’s a car, a bike, or a pedestrian.

**Kalman Filters** are a very popular technique used to estimate the state of a system. Kalman Filters estimate a **continuous state**, and give us a **Uni-Modal distribution**. Finding out what state you are in in **discrete** states is done with **Monte Carlo Localization**.



If an object is being tracked at the given positions, and we need to estimate the position at t=4, we can assume that given the velocity of the data give, the prediction would follow in the same direction. These are the types of observations a Kalman Filter has. It estimates future positions, and velocities. Kalman filters are useful for these continuous situations.

**Gaussian**

In Kalman Filters, the probability distribution (of estimates) is given by a Gaussian. A Gaussian is a continuous function that has an area underneath that sums up to 1.

The Gaussian is characterized by the mean and the variance (In 1-D).

Kalman filters want to maintain a mean and variance as the best estimate of the location we are trying to find.



Gaussians have a single peak (Uni-modal), and are symmetric.

Variance is a good measure of uncertainty. The larger it is, the more uncertain we are about the actual state the Kalman Filter is estimating.

This means we want a Gaussian that is thin, meaning the uncertainty is low for a state.

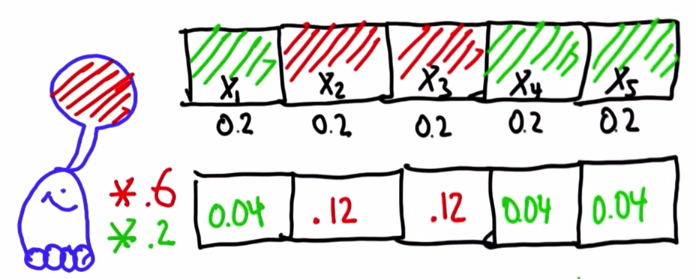
To find the max value of a Gaussian, choose the value of X equal to the mean, making the exponential value 1, and just leaving the magnitude.

**A Kalman Filter represents the distributions by Gaussians and iterates on two main cycles.**

**The First Cycle is the Measurement Update.**

It uses Bayes Rule, Which requires a product.

Example. Given an observation of red, and 5 possible states of which 3 are green and 2 are red. What is the probability that we are in each state. This can be solved with Bayes Rule. A much larger value (0.6) is chosen for red due to the measurement of Red being seen.



These values are then normalized to add up to 1. They are normalized by the sum of all the current values.

After they are normalized, we have a proper probability distribution.

**The Second Cycle is the Motion Update.**

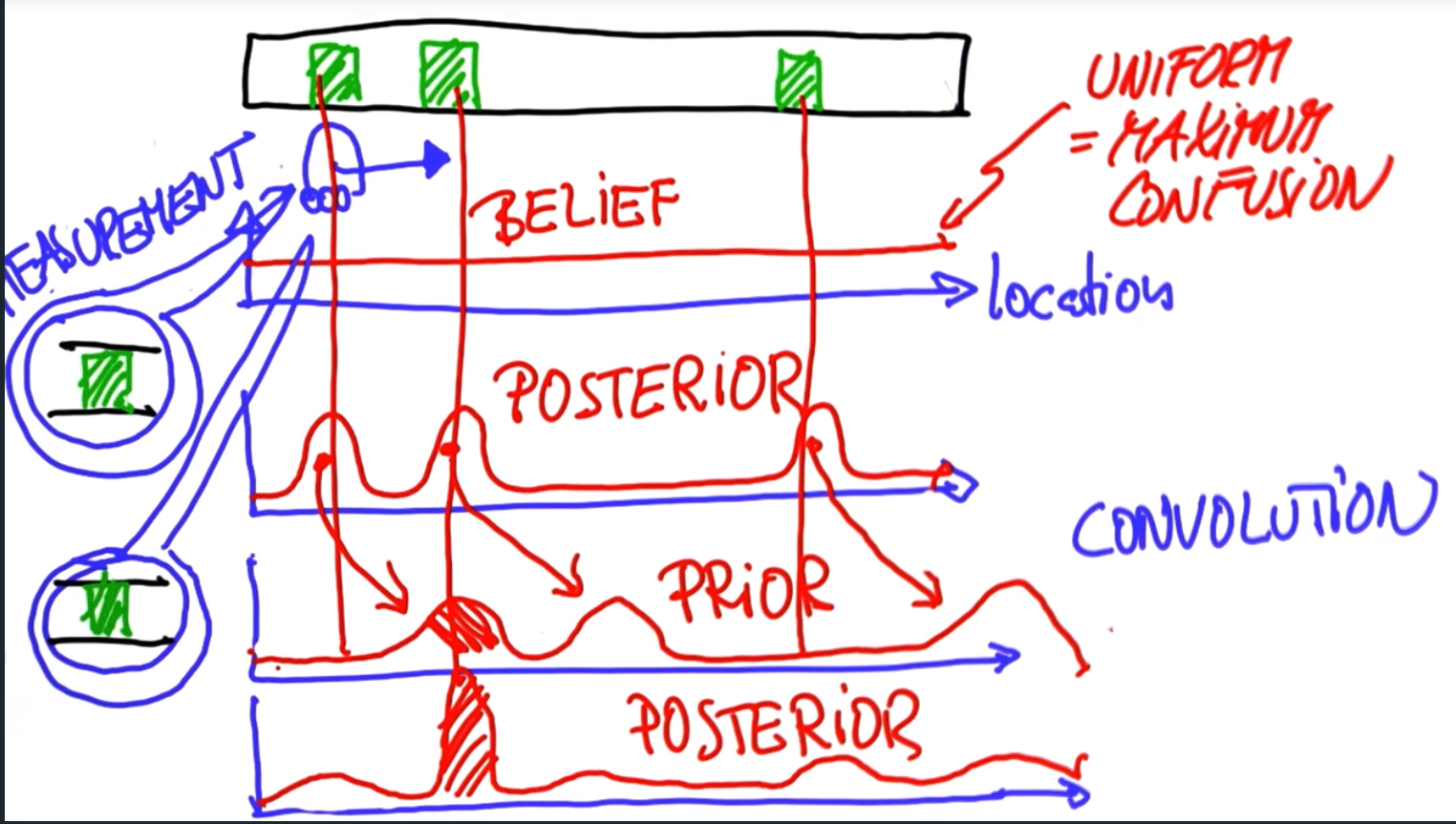
This uses Total Probability, which involves convolution.

Example.

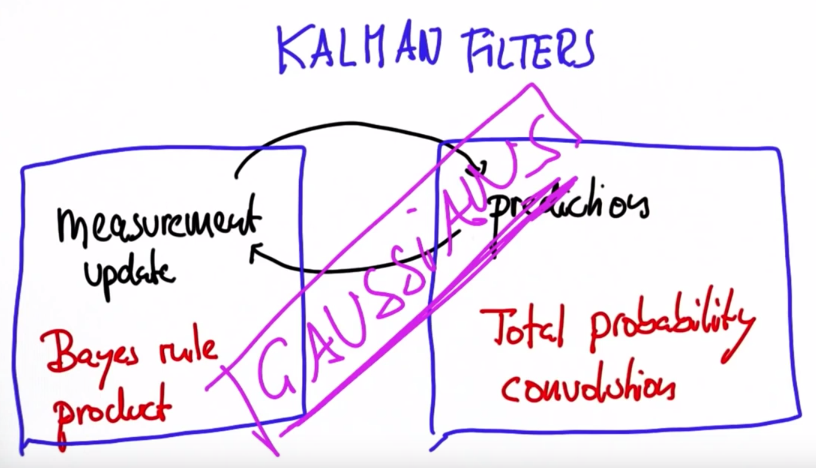
If we have a space where a robot could be, and the probability that the robot could be in any space is equal (Probability Distribution is Equal), it is called the State of Maximum Confusion.

To localize from this situation, a robot would look at landmarks. If a robot observes that it stands in front of a door changes the distribution of the possible locations. Locations near doors have an increased belief, meaning that locations without a door have a decreased belief.

As the robot moves and senses again, there is a shift in the belief distribution. This is called a Convolution. If the robot measures it is near a door a second time, while knowing how far it moved, Convolution of both belief distributions can be used to find the final localized position.

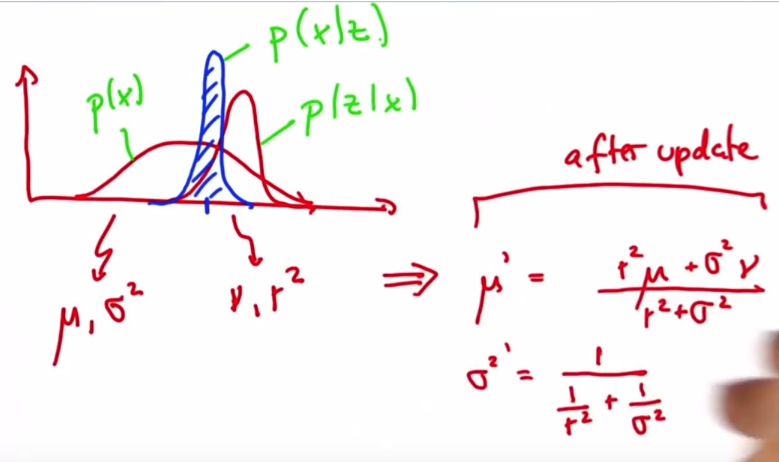


The final distribution is a good localization of where the robot is.

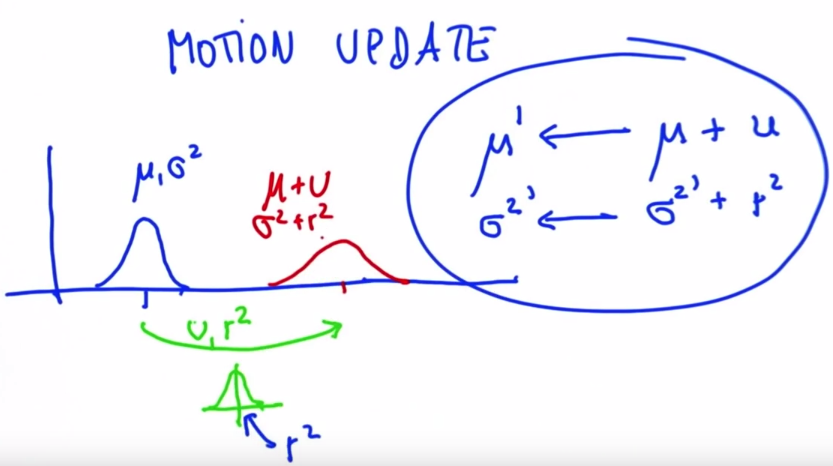


If we have a prior distribution of probability, and we have a measurement Guasian, measurement where the mean is shifted, the new mean prediction (posterior) is somewhere in between the two, but closer to the distribution that has a smaller variance.

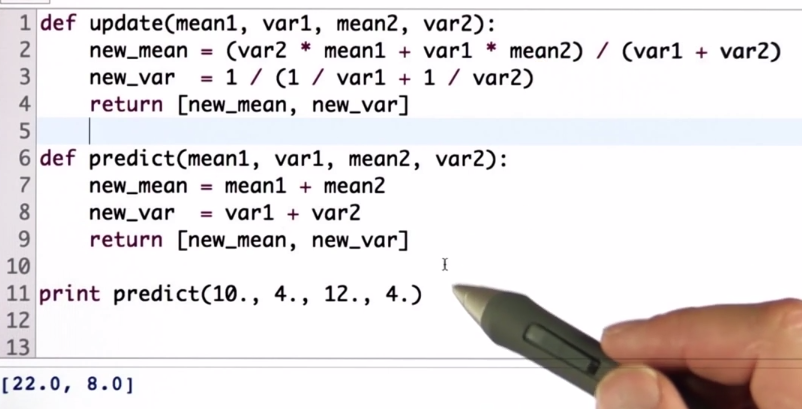
The peak of the predicited distribution is always higher than the measurement and the prior. This is because the more measurements we make, the more certain our new belief is. (Meaning the variance is smaller).



No matter the distribution, the more measurements, the smaller the variance of the prediction.



Example of a 1 dimensional Kalman Filter:



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