* 1. Maximum likelihood estimator

(Skip-But Later will review this) Maximum likelihood estimator

* 1. **The Discrete-Time Kalman Filter: Conditional Mean Estimator**
* Problem: A dynamic system given as

1. We measure
2. The conditional estimator (the MV estimator) is
3. The propagated estimator is

* *The propagated estimator:*

= a Priori Estimator / a Predicted estimator

= measurements are previous compared to a posteriori estimator

* *general text book notations are as follows*
* The Estimator
* The Predictor 🡪 the upper accents are different ~~

1. Propagating the conditional mean = a priori = prediction

* Remember , not

1. Propagating the variance of the a prior
2. Updating the Conditional Mean: a posterior

* Remember not

1. Updating the covariance: a posteriori

* Define: **Residual 🡪 innovation sequence**

From (3.44)

* Define Kalman Gain: the residual gain :

Hence (3.44.1) is

* Orthogonality Properties of the Conditional Mean Estimator

1. The Innovation Sequence is independent for each

Since, the mean of ,

And,

with these facts, therefore the covariance is

which implies the gaussian are independent.

1. Error is orthogonal to ,

* Example 3.9 (estimating the speed of a car)
* Problem: estimate traveled distance by car.

1. The speed of car = 55 mi/hr, for 1 hour, implies the distance is 55 mi
2. The trip meter shown 55.3 mi

What is the best estimated distance with two information?

* Method

1. The system is modelled as
2. We may guess
3. The variance by the measurement: the quantization of the trip meter is = 0.1(mi) 🡪 The variance of the trip meter ,
4. The variance by the process: the velocity varies +/- 1 (mi/hr), the variance of the process
5. The best estimator of the distance in mean square sense,
6. Comments:  
   - the variance of a uniform RV in (a,b) is

-. Compare