

ASEN 5070  
Statistical Orbit Determination I  
Fall 2012



Professor Jeffrey S. Parker  
Professor George H. Born

Lecture 27: Final Lecture!



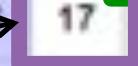
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# Announcements

- ▶ Today's the final lecture!
- ▶ Check your grades (for those graded anyway), especially quizzes.
- ▶ Exam 3 out today – due Monday at midnight unless you get permission otherwise.
- ▶ Thursday work day in this room.
- ▶ Everything else due Dec 20. Let me know if this is a problem!

December 2012						
Sun	Mon	Tue	Wed	Thu	Fri	Sat
					1	
2	3	4	5	6	7	8
9	10	11	12	13	14	15
16	17	18	19	20	21	22
23	24	25	26	27	28	29
30	31					

Take-Home  
Exam Due



Final Project  
Due  
All HW Due



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# Review Topics

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- ▶ The Art of Stat OD
- ▶ Probability and Statistics
- ▶ The Process
  
- ▶ Then we'll conclude with a final visit of spaceflight operations in practice.



# The Art of Stat OD

## ► Set up your scenario

- What are you estimating?
- Set up  $\mathbf{X}(t)$      $\dot{\mathbf{X}}(t)$
- What observations do you have?
- Set up  $\mathbf{Y}(t)$      $\mathbf{G}(t)$      $R(t)$  or  $W(t)$
- Do you have any *a priori* information?  
 $\bar{\mathbf{x}}(t_0)$      $\bar{P}(t_0)$
- Any consider parameters?



# The Art of Stat OD

## ► Set up your scenario

- What are the dynamics?

$$\dot{\mathbf{X}}(t) = \mathbf{F}(\mathbf{X}(t), t) \quad \dot{\Phi}(t, t_0) = A\Phi(t, t_0)$$

- What are the observation state equations?

$$\mathbf{y} = H\mathbf{x} + \epsilon \quad \tilde{H}(t)$$



# The Art of Stat OD

- ▶ Select a Filter
  - Least Squares
  - Weighted Least Squares
  - Minimum-Variance with *a priori*
  - P-Norm Filters
  
- ▶ Select an algorithm
  - Batch
  - Conventional Kalman
  - Extended Kalman
  - Others



# The Art of Stat OD

- ▶ Make adjustments to account for numerical issues
  - Joseph formulation to help the P matrix
  - Square root processes to keep P positive definite
    - Potter, Cholesky, Givens, Householder
    - Also improves the conditioning of any matrices
    - Square root free algorithms to speed up numerical computations
  - Process noise compensation to avoid filter saturation
    - State Noise Compensation
    - Dynamical Model Compensation



# Analysis

- ▶ After processing your observations, observe the results.
  - Is everything observable?
  - Did the covariance collapse? Diverge?
  - Do the post-fit residuals appear Gaussian?
    - If not, perhaps you need to adjust the tuning parameters or the dynamical model.
- ▶ How do the results compare with other solutions?
  - Try out all sorts of set-ups, arcs, etc, to see if everything is consistent.
  - Can you safely reduce the amount of tracking in the future?
  - Are you meeting your scientific/engineering objectives?



# Review Topics

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- ▶ ~~The Art of Stat OD~~
- ▶ Probability and Statistics
- ▶ The Process
  
- ▶ Then we'll conclude with a final visit of spaceflight operations in practice.



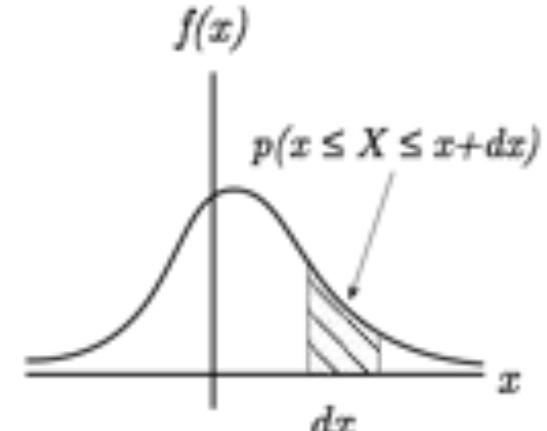
# Probability and Statistics

- ▶ Why do we care?
- ▶ We need to know something about the expected value and distribution of an error!
- ▶ Given:
  - An uncertain state (hopefully with a corresponding covariance)
  - Noisy observations
  - Errors in dynamical model
- ▶ We'd like to know what the “expected value” and “variance–covariance” of our state estimation errors are!

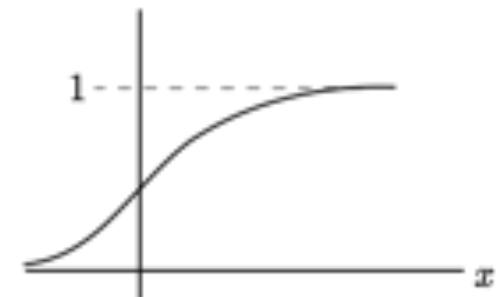


# Probability and Statistics

- ▶ What is a probability density function?
- ▶ What is a cumulative distribution function?



Density function of a continuous random variable  
 $F(x)$



Distribution function of a continuous random variable



# Probability and Statistics

- ▶ What is a conditional probability function?

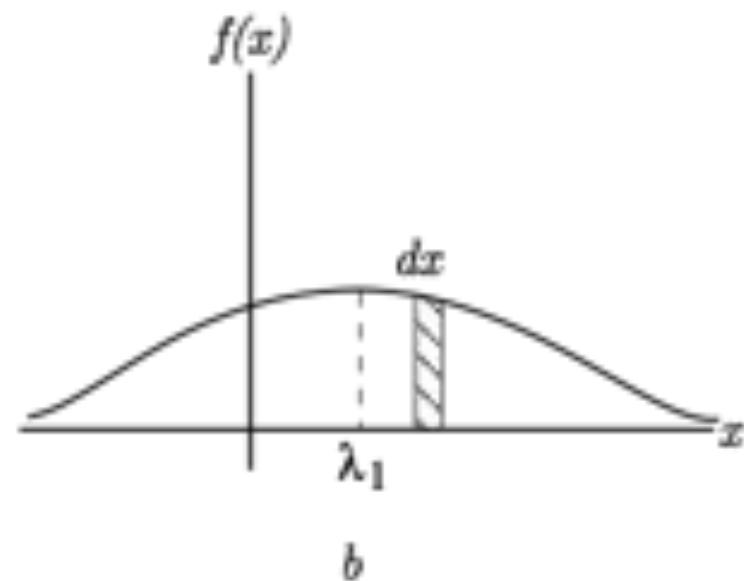
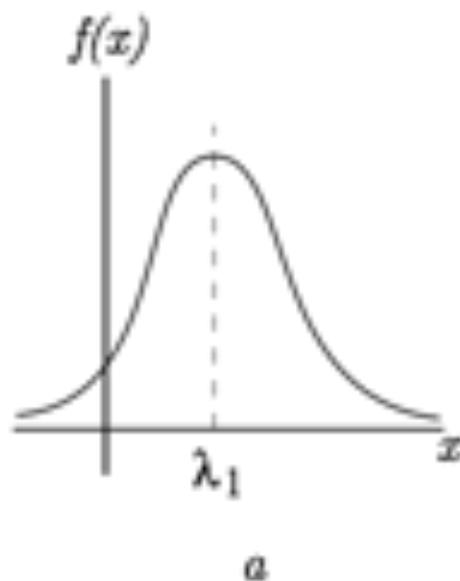
$$p(B/A) = \frac{p(AB)}{p(A)}$$

- ▶ Why do we care?
  - Bayesian statistics
  - We want to be able to compute the best estimate of our state in the presence of our observations!



# Expected Value and Variance

- Given a probability density function, we'd like to be able to compute  $E[x]$  and  $E[(x-\bar{x})(x-\bar{x})^T]$

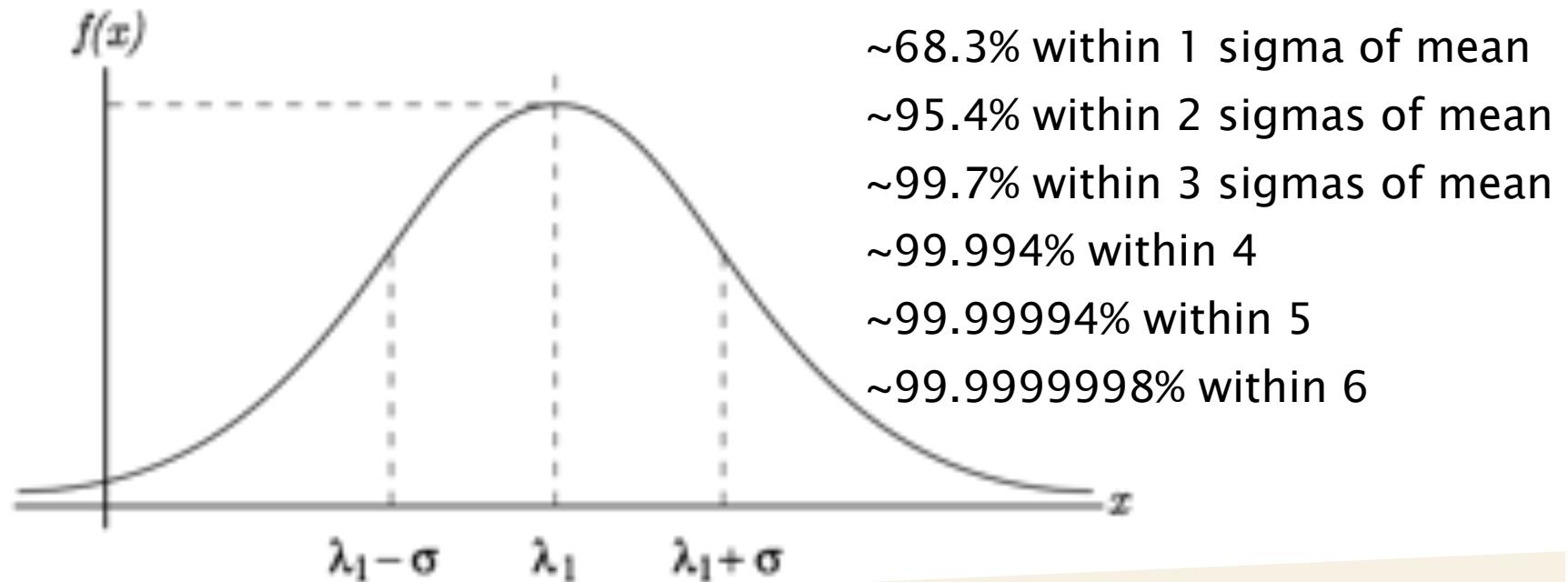


# The Gaussian or Normal Density Function

One of the most important density functions is the Gaussian.

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} \exp\left[-\frac{1}{2}\left(\frac{x-\lambda_1}{\sigma}\right)^2\right] -\infty < x < \infty . \quad (\text{A.8.7})$$

- The Gaussian density function is depicted graphically as



# Variance-Covariance Matrix

$$P = E[(\mathbf{x} - \bar{\mathbf{x}})(\mathbf{x} - \bar{\mathbf{x}})^T]$$

The variance-covariance matrix for an  $n$ -dimensional random vector,  $X$ , can be written as

$$P = \begin{bmatrix} \sigma_1^2 & \rho_{12}\sigma_1\sigma_2 & \cdots & \rho_{1n}\sigma_1\sigma_n \\ \rho_{12}\sigma_1\sigma_2 & \sigma_2^2 & \cdots & \rho_{2n}\sigma_2\sigma_n \\ \vdots & \ddots & \ddots & \vdots \\ \rho_{1n}\sigma_1\sigma_n & \rho_{2n}\sigma_2\sigma_n & \cdots & \sigma_n^2 \end{bmatrix} \quad (\text{A.14.3})$$

where  $\rho_{ij}$  is a measure of the degree of linear correlation between  $X_i$  and  $X_j$ .



# Review Topics

---

- ▶ ~~The Art of Stat OD~~
- ▶ ~~Probability and Statistics~~
- ▶ The Process
  
- ▶ Then we'll conclude with a final visit of spaceflight operations in practice.



# Fitting the data

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- ▶ How do we best fit the data?
- ▶ A good solution, and one easy to code up, is the least-squares solution

$$\text{Minimize } J = \frac{1}{2} \epsilon^T \epsilon$$

$$\frac{\partial J}{\partial X} = 0$$

$$\frac{\partial^2 J}{\partial^2 X}$$
 is positive definite

# Fitting the data

- ▶ How do we best fit the data?

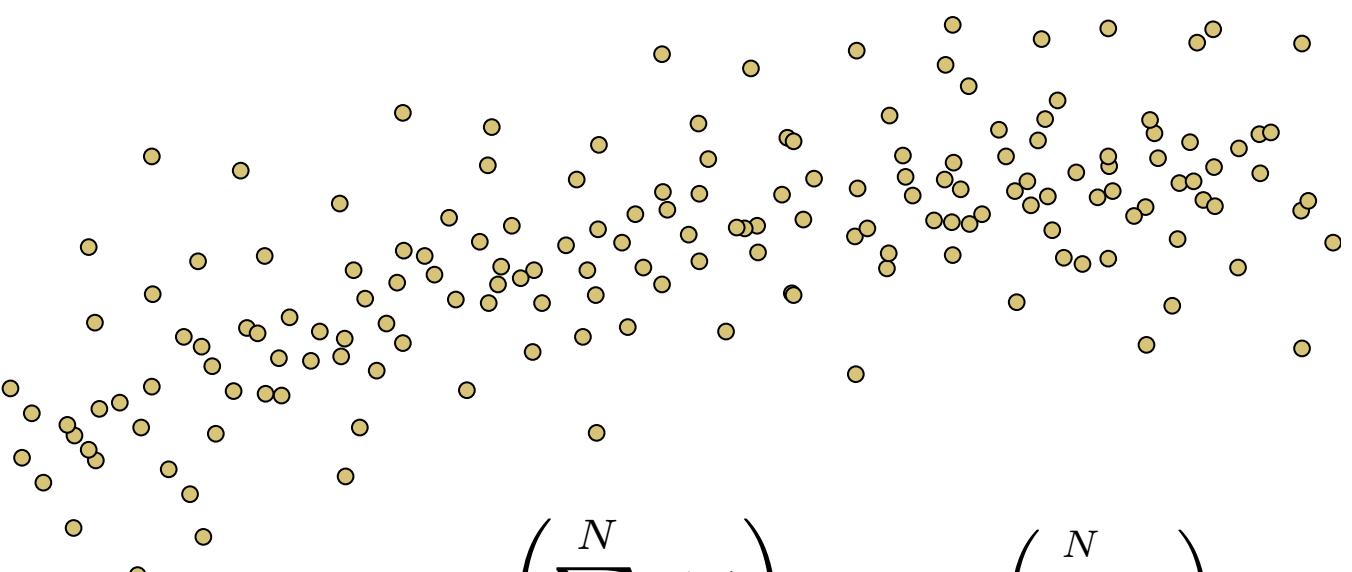
Residuals =  $\epsilon = O-C$

$$\min \left( \sum_{i=1}^N \epsilon_i \right) ? \quad \text{No}$$

$$\min \left( \sum_{i=1}^N \epsilon_i \right)^2 ? \quad \text{No}$$

$$\min \left( \sum_{i=1}^N |\epsilon_i| \right) ? \quad \text{Not bad}$$

$$\min \left( \sum_{i=1}^N \epsilon_i^2 \right) ?$$



$$\min \left( \sum_{i=1}^N \epsilon_i^{1.4} \right) ? \quad \min \left( \sum_{i=1}^N \epsilon_i^4 \right) ?$$



# State Deviation and Linearization

- ▶ Linearization
- ▶ Introduce the state deviation vector

$$\mathbf{x}(t) = \mathbf{X}(t) - \mathbf{X}^*(t)$$

- ▶ If the reference/nominal trajectory is close to the truth trajectory, then a linear approximation is reasonable.



# State Transition Matrix

- ▶ The state transition matrix maps a deviation in the state from one epoch to another.

$$\mathbf{x}(t_2) = \Phi(t_2, t_1)\mathbf{x}(t_1)$$

$$\Phi(t_2, t_1) = \Phi(t_1, t_2)^{-1}$$

- ▶ It is constructed via numerical integration, in parallel with the trajectory itself.

$$\dot{\Phi}(t, t_0) = A(t)\Phi(t, t_0)$$

$$\Phi(t_0, t_0) = I$$



# Measurement Mapping Matrix

$$\mathbf{y}(t) = \tilde{H}(t)\mathbf{x}(t) + \epsilon(t)$$

## ► The Mapping Matrix

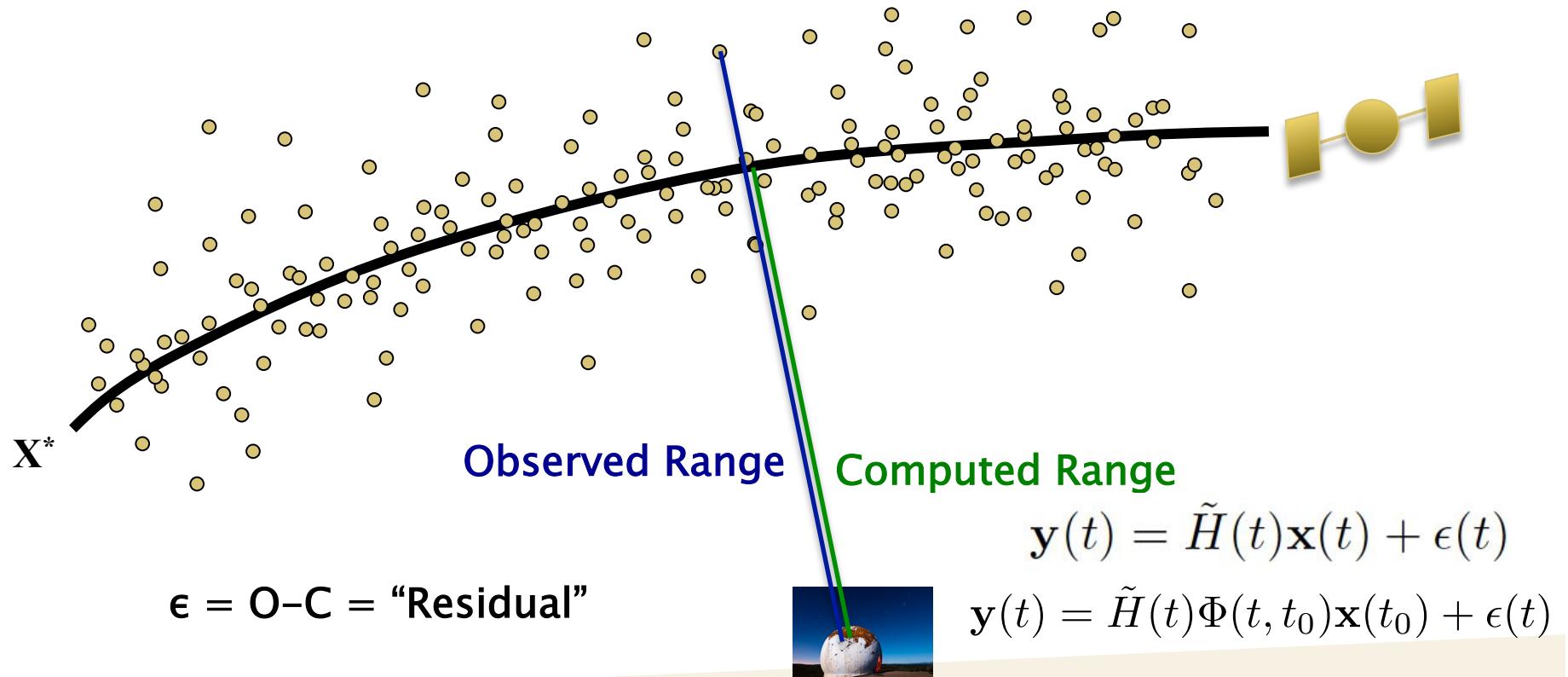
$$\tilde{H}(t) = \frac{\partial \mathbf{h}(t, \mathbf{X}(t))}{\partial \mathbf{X}(t)}$$

$$\tilde{H}(t) = \begin{bmatrix} \frac{\partial \rho}{\partial x} & \frac{\partial \rho}{\partial y} & \dots & \frac{\partial \rho}{\partial z} \\ \frac{\partial \dot{\rho}}{\partial x} & \frac{\partial \dot{\rho}}{\partial y} & \dots & \frac{\partial \dot{\rho}}{\partial z} \\ \frac{\partial \ddot{\rho}}{\partial x} & \frac{\partial \ddot{\rho}}{\partial y} & \dots & \frac{\partial \ddot{\rho}}{\partial z} \end{bmatrix}$$



# Mapping an observation

- After these mapping matrices are defined, we can relate an observation to the satellite's state at any epoch!



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# Different ways to get a *best estimate*

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- ▶ Least Squares

$$\hat{\mathbf{x}}_k = (H^T H)^{-1} H^T \mathbf{y}$$

- ▶ Weighted Least Squares

$$\hat{\mathbf{x}}_k = (H^T W H)^{-1} H^T W \mathbf{y}$$

- ▶ Least Squares with *a priori*

$$\hat{\mathbf{x}}_k = (H^T W H + \bar{W}_k)^{-1} (H^T W \mathbf{y} + \bar{W}_k \bar{\mathbf{x}}_k)$$

- ▶ Min Variance

$$\hat{\mathbf{x}}_k = (H^T R^{-1} H)^{-1} H^T R^{-1} \mathbf{y}$$

- ▶ Min Variance with *a priori*

$$\hat{\mathbf{x}}_k = (\tilde{H}_k^T R^{-1} \tilde{H}_k + \bar{P}_k^{-1})^{-1} (\tilde{H}_k^T R^{-1} \mathbf{y}_k + \bar{P}_k^{-1} \bar{\mathbf{x}}_k)$$

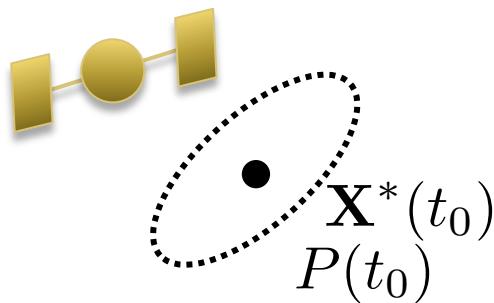


# Review of the Stat OD Process

## ► Setup.

- Given: an initial state  $\mathbf{X}^*(t_0)$
- Optional: an initial covariance  $P(t_0)$

$$\mathbf{X}^*(t_0) = [ x_0, y_0, z_0, \dot{x}_0, \dot{y}_0, \dot{z}_0, c_1, c_2 ]^T$$



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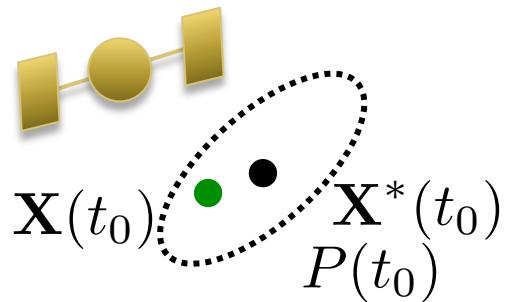
# Review of the Stat OD Process

## ► Setup.

- Given: an initial state  $\mathbf{X}^*(t_0)$
- Optional: an initial covariance  $P(t_0)$

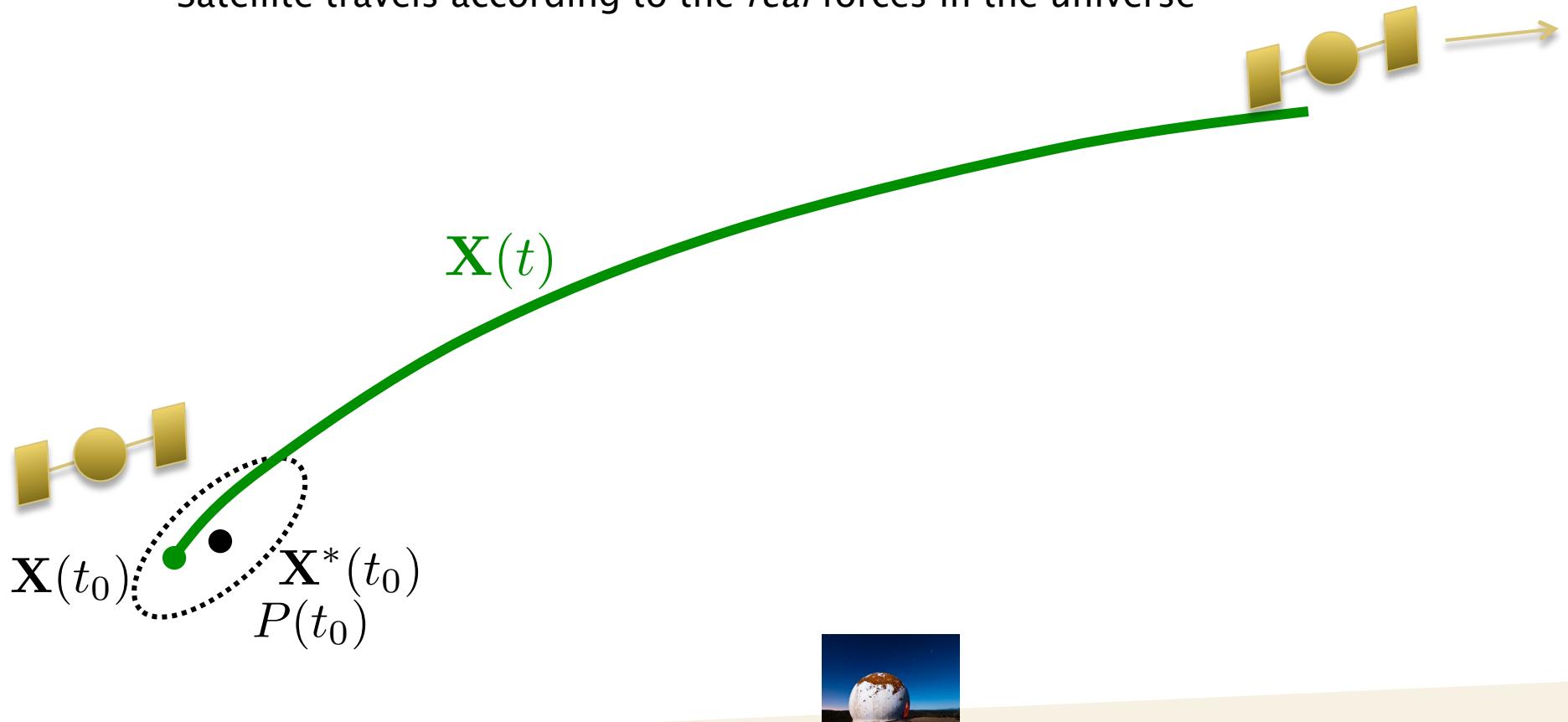
$$\mathbf{X}^*(t_0) = [x_0, y_0, z_0, \dot{x}_0, \dot{y}_0, \dot{z}_0, c_1, c_2]^T$$

- The satellite will *not* be there, but will (hopefully) be nearby
  - True state =  $\mathbf{X}(t_0)$



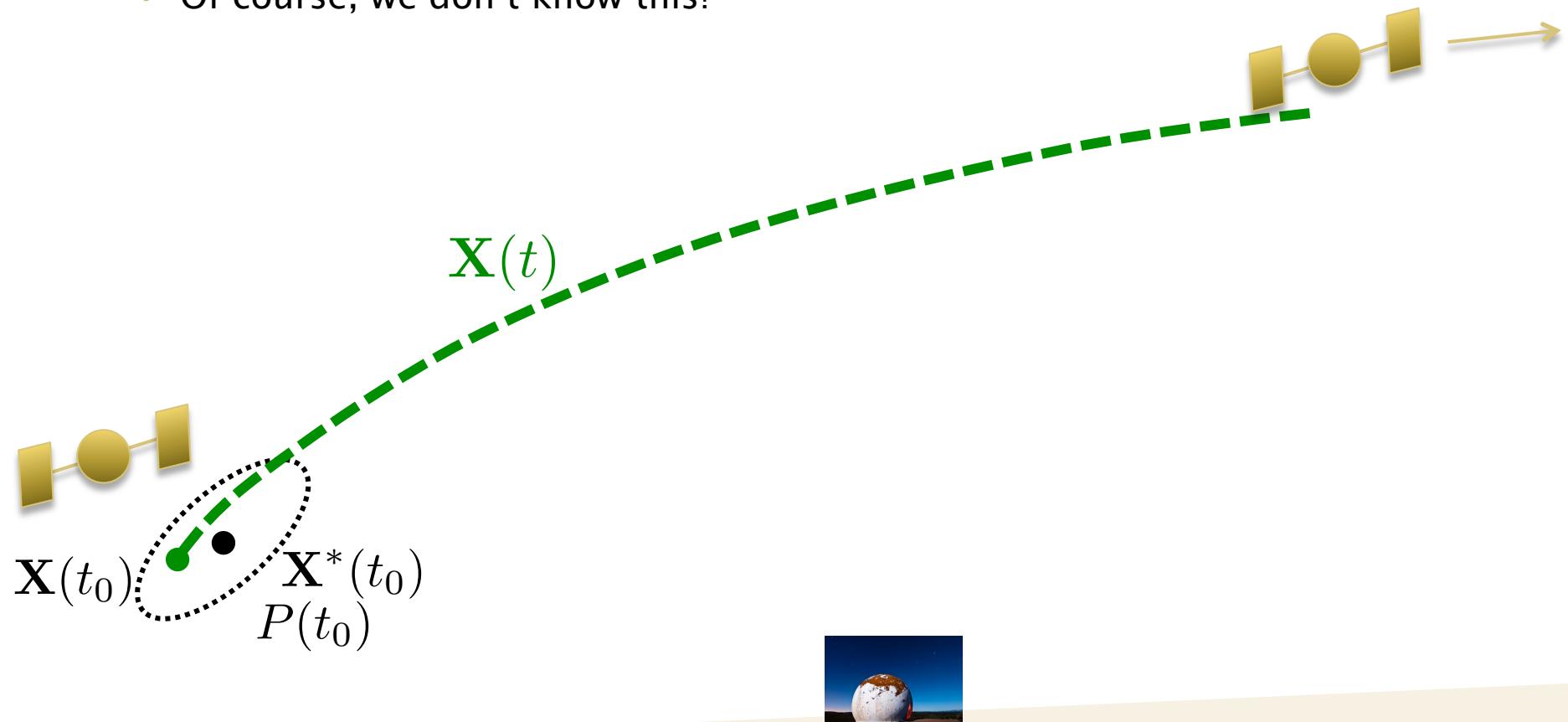
# Review of the Stat OD Process

- ▶ What really happens
  - Satellite travels according to the *real* forces in the universe



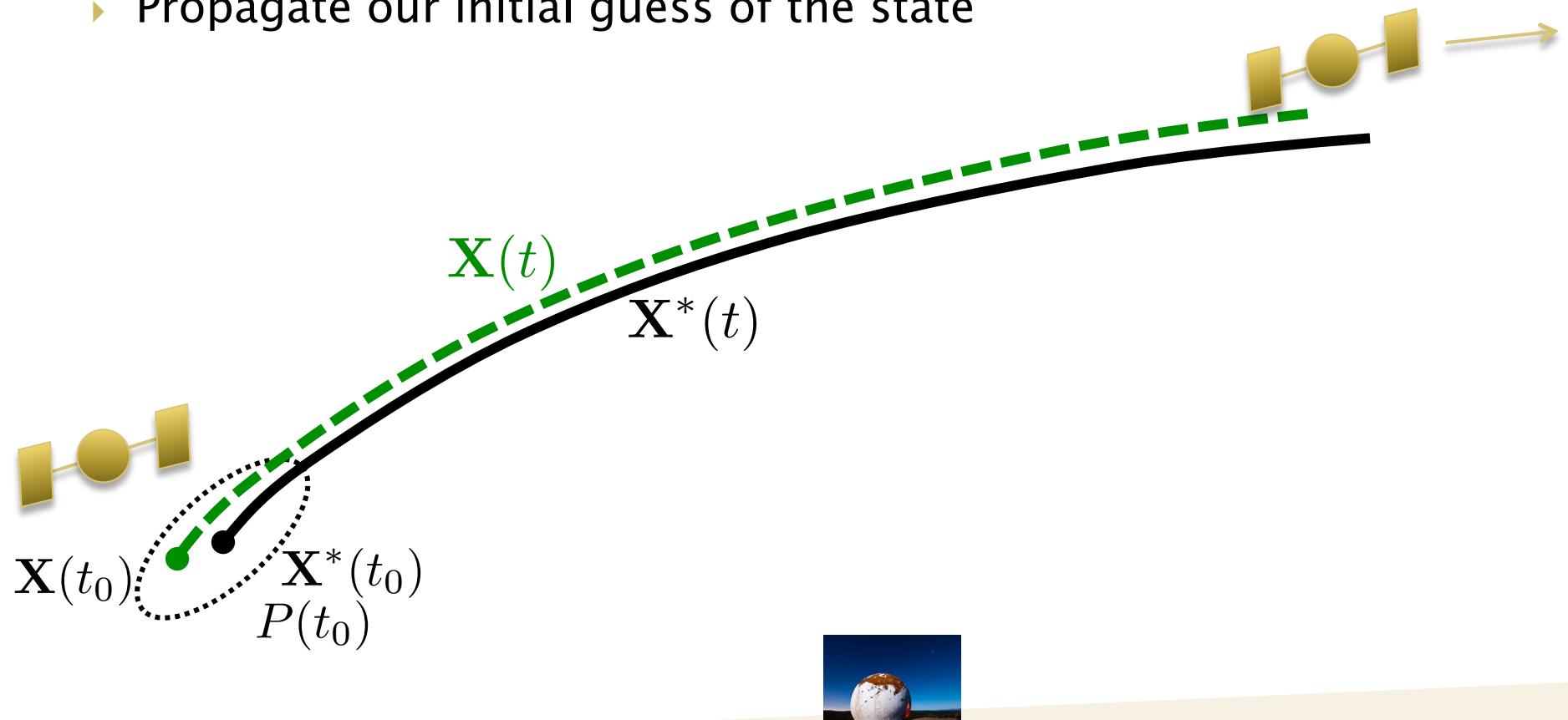
# Review of the Stat OD Process

- ▶ What really happens
  - Of course, we don't know this!



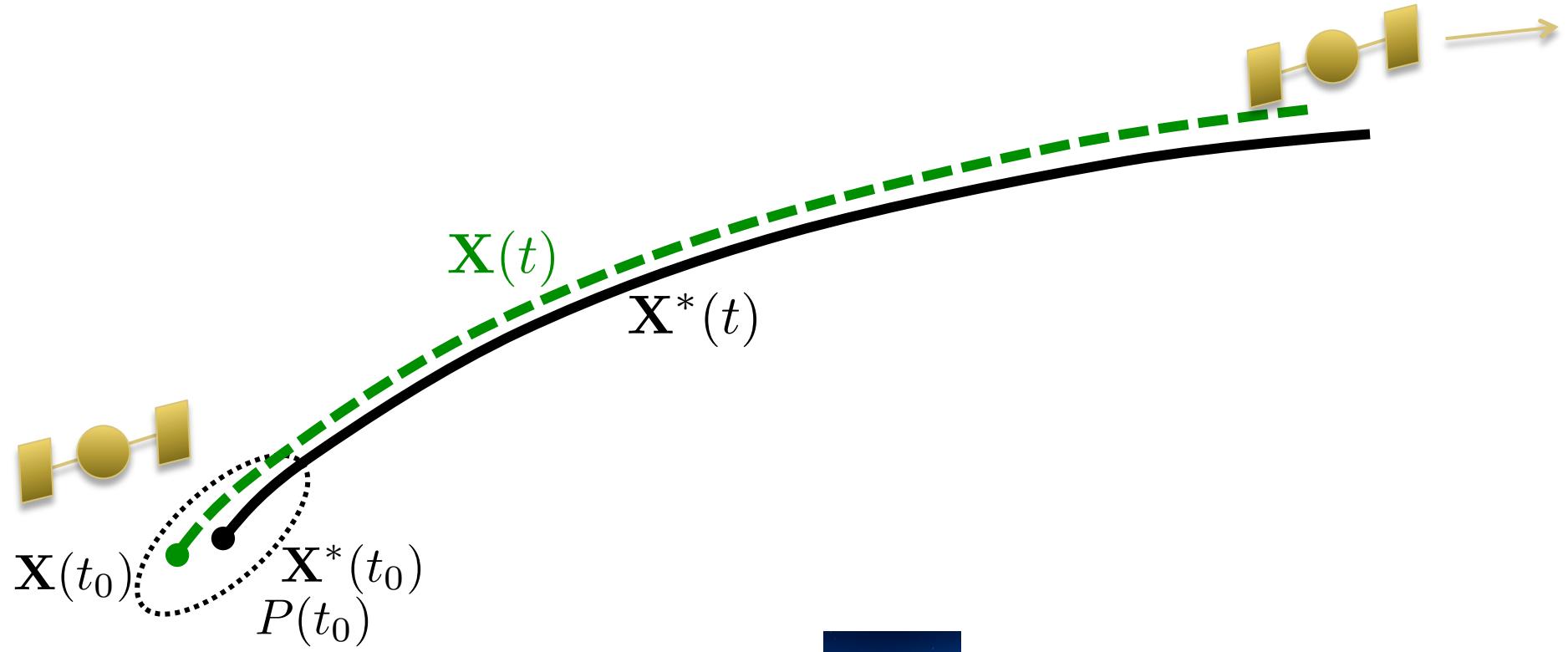
# Review of the Stat OD Process

- ▶ Model reality as best as possible
- ▶ Propagate our initial guess of the state



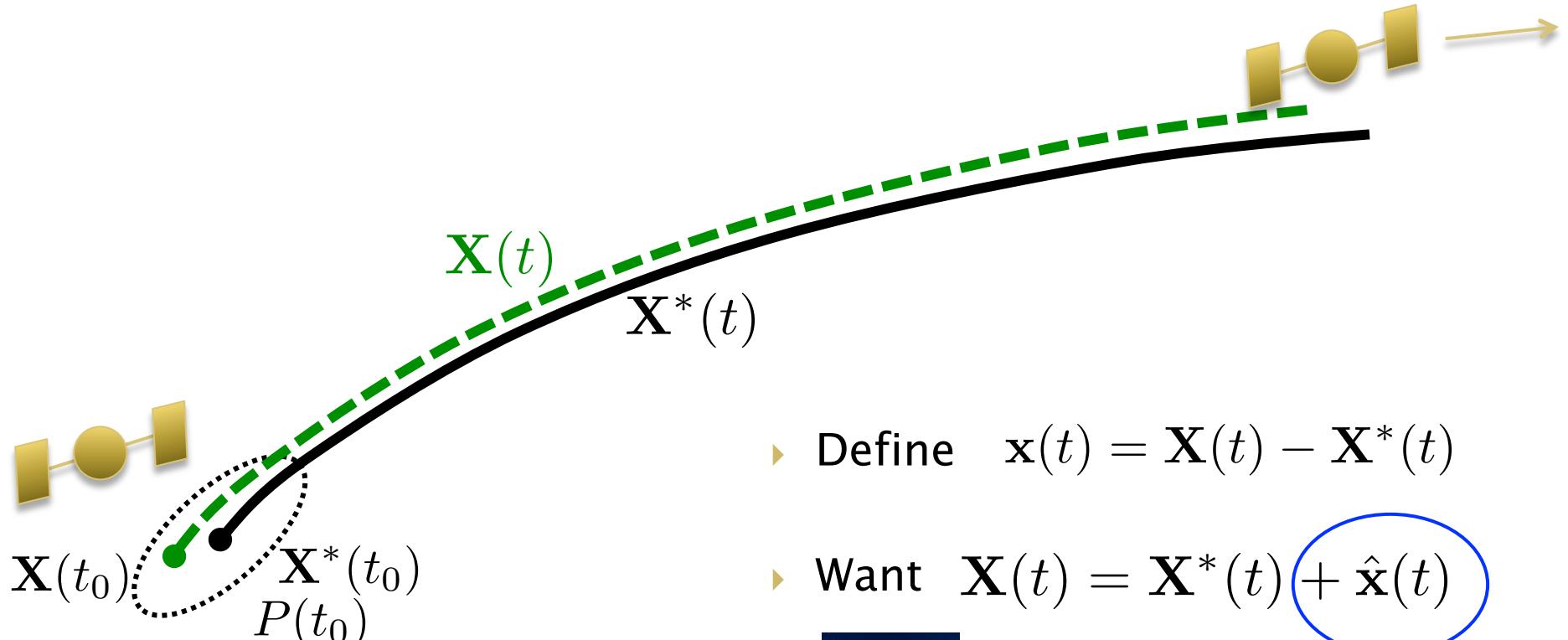
# Review of the Stat OD Process

- ▶ Goal: Determine how to modify  $\mathbf{X}^*(t)$  to match  $\mathbf{X}(t)$



# Review of the Stat OD Process

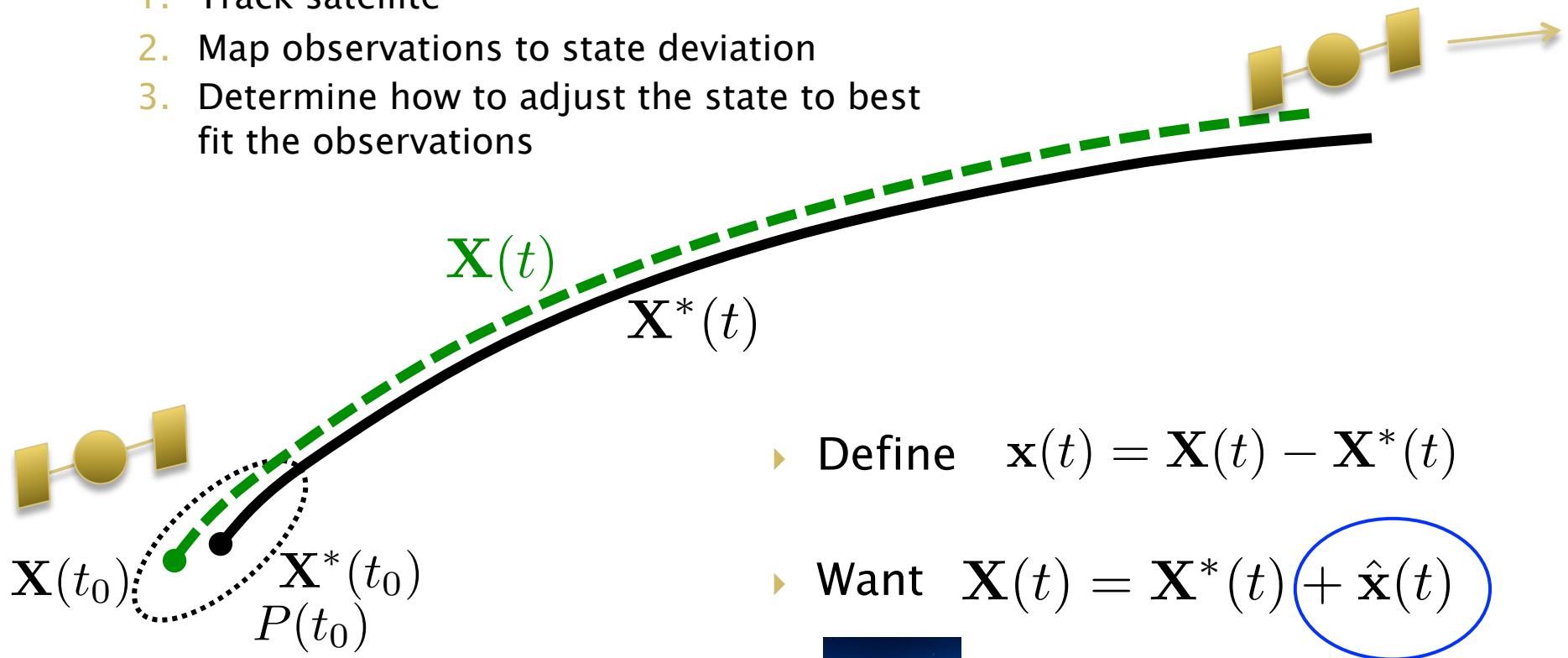
- ▶ Goal: Determine how to modify  $\mathbf{X}^*(t)$  to match  $\mathbf{X}(t)$



# Review of the Stat OD Process

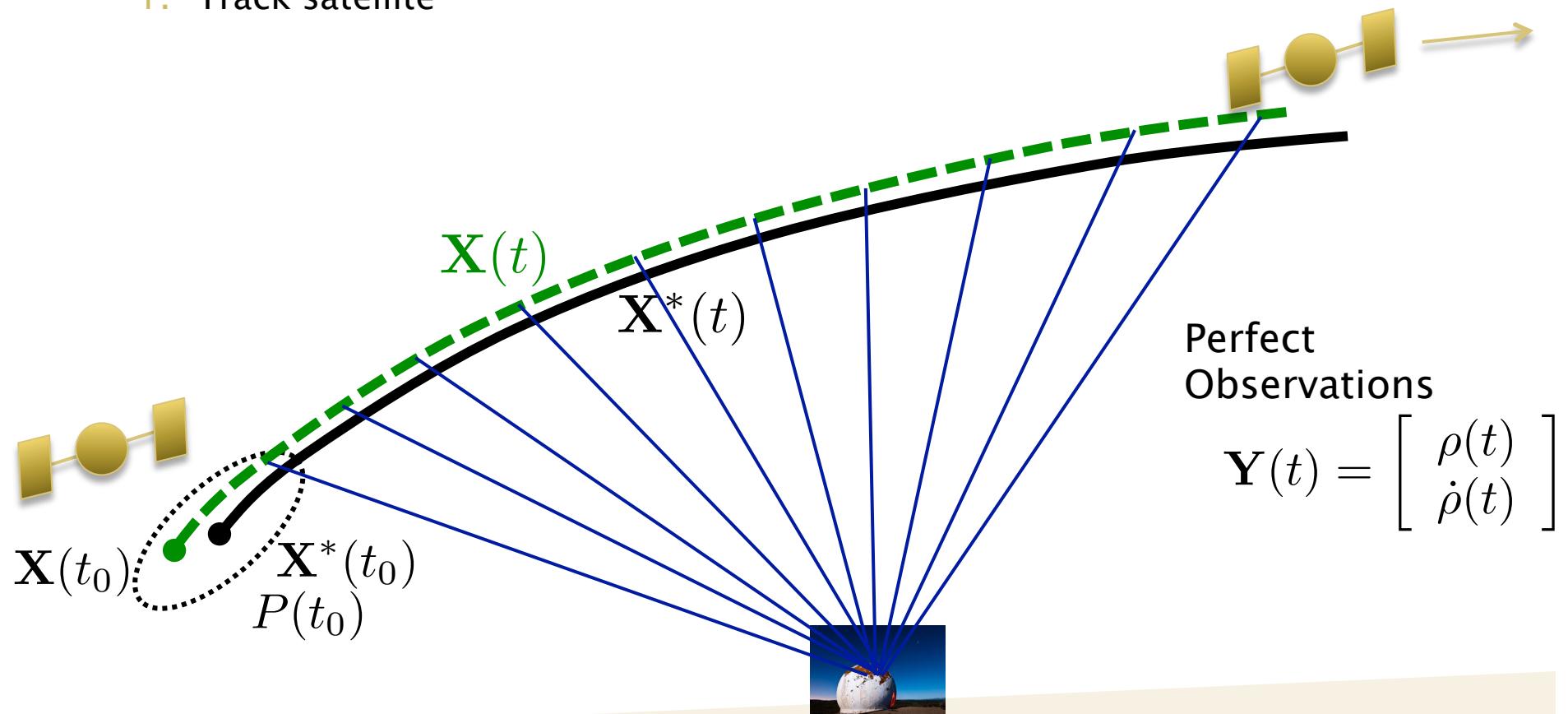
- ▶ **Process:**

1. Track satellite
2. Map observations to state deviation
3. Determine how to adjust the state to best fit the observations



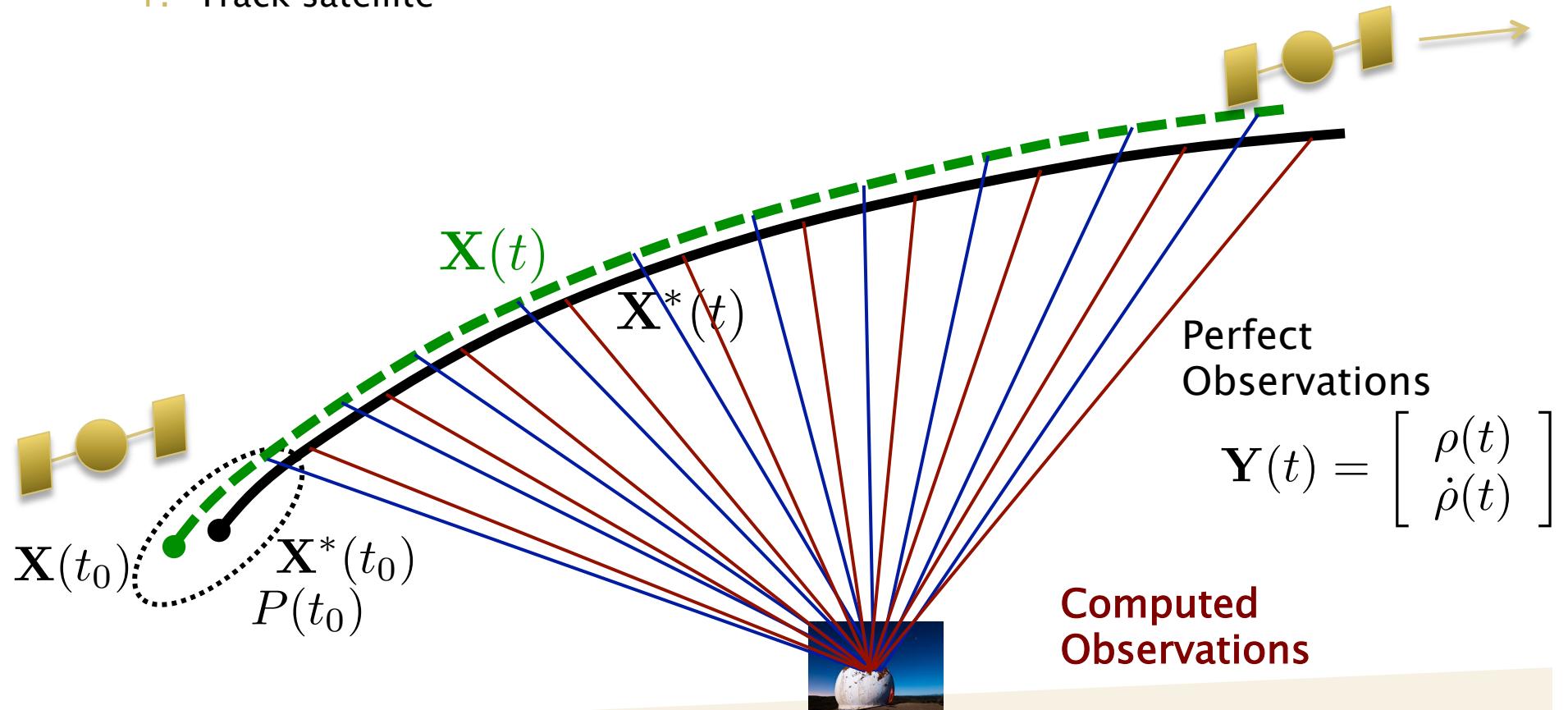
# Review of the Stat OD Process

- ▶ Process:
  1. Track satellite



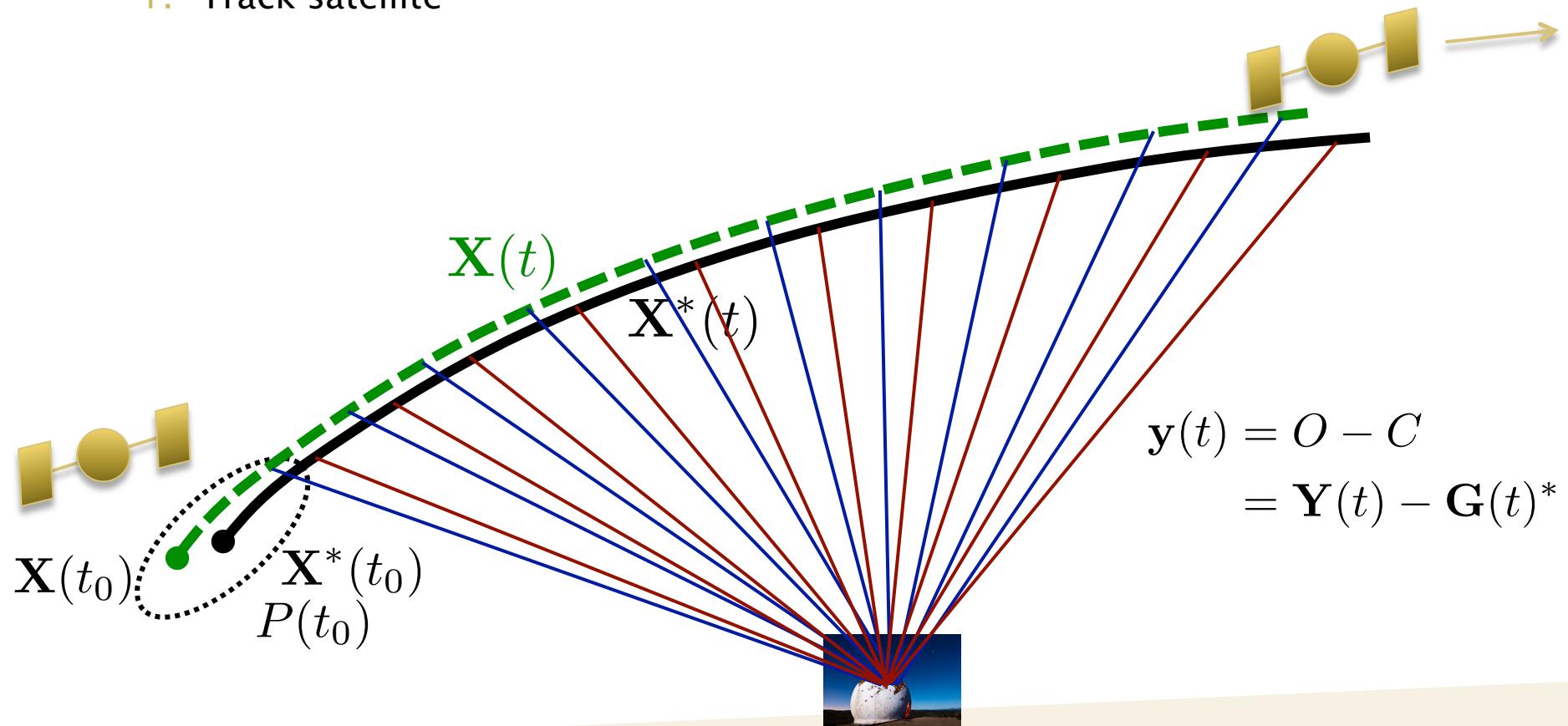
# Review of the Stat OD Process

- ▶ Process:
  1. Track satellite



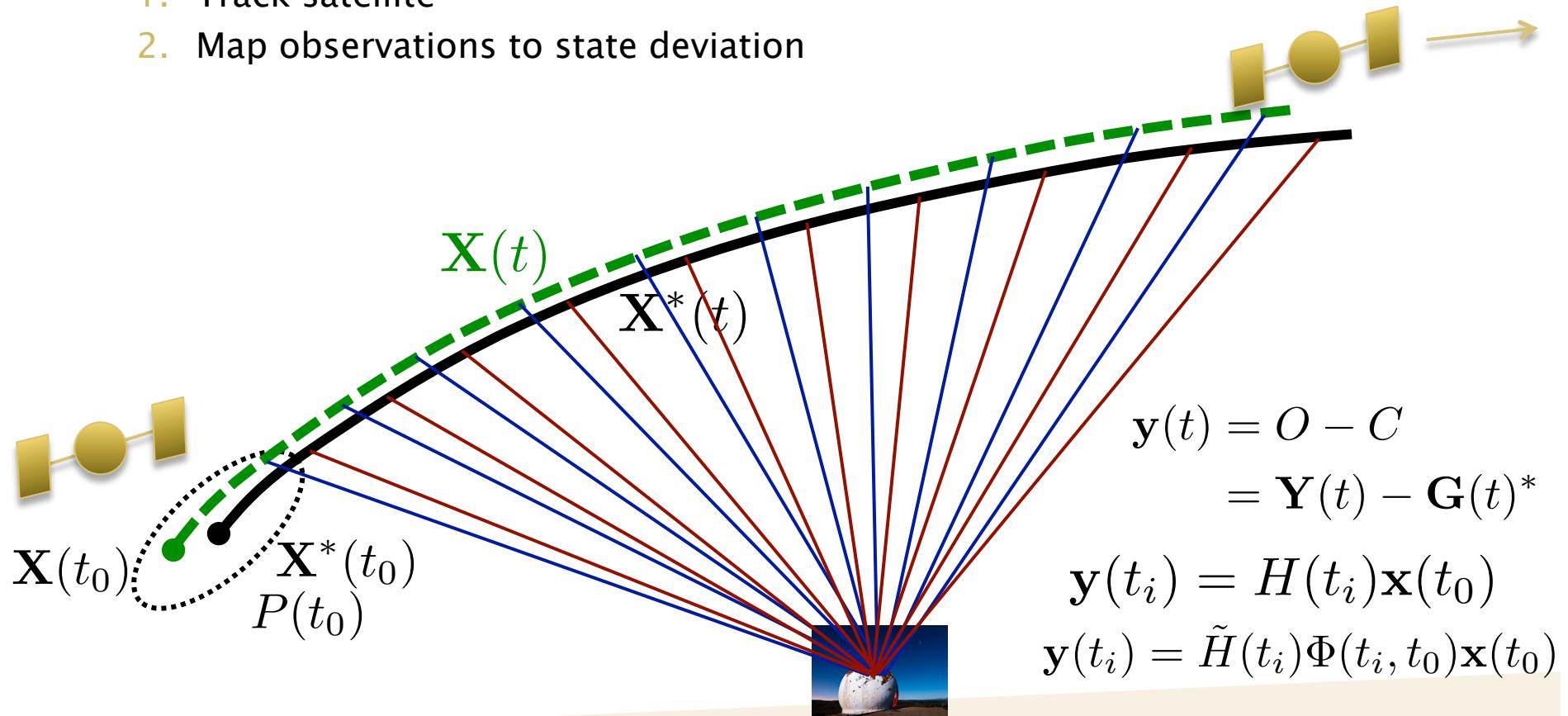
# Review of the Stat OD Process

- ▶ Process:
  1. Track satellite



# Review of the Stat OD Process

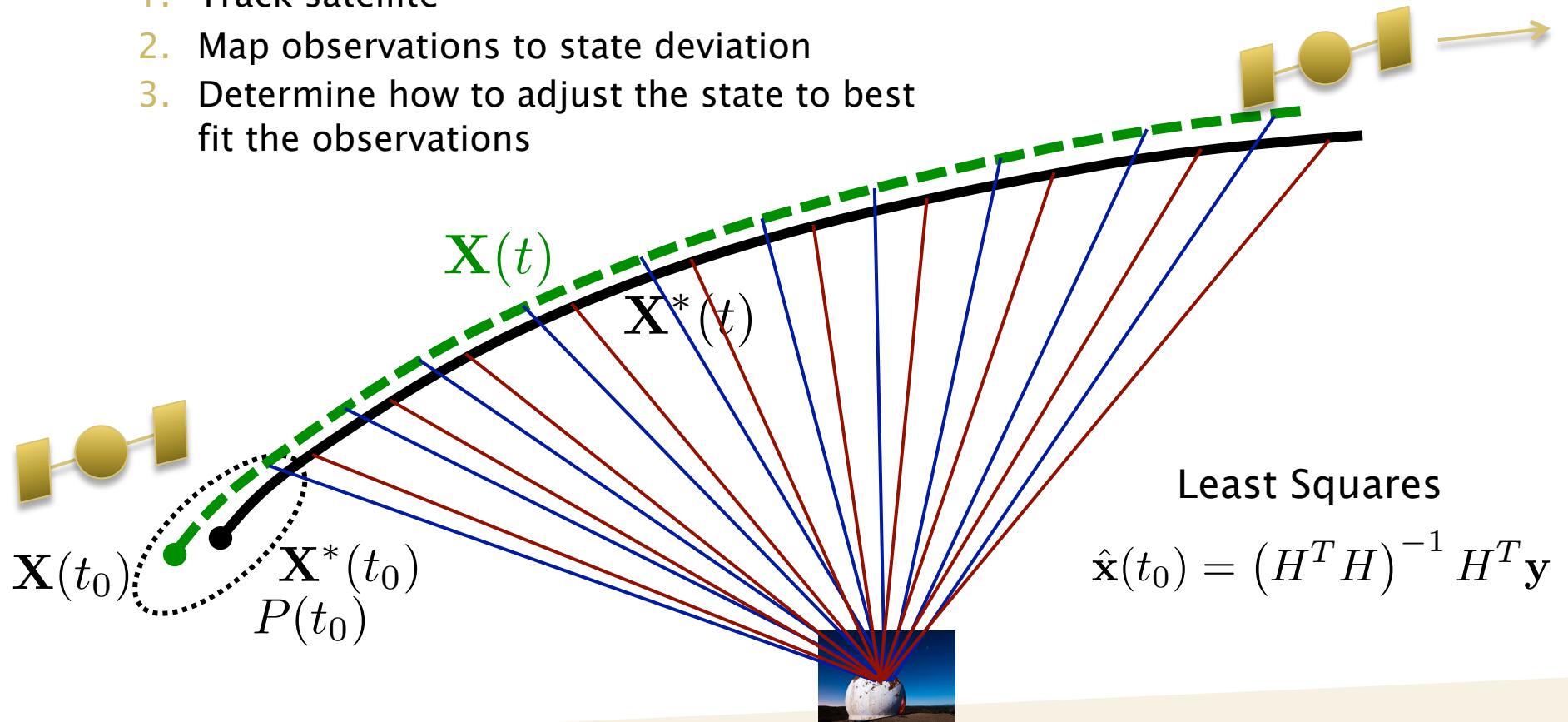
- ▶ Process:
  1. Track satellite
  2. Map observations to state deviation



# Review of the Stat OD Process

## Process:

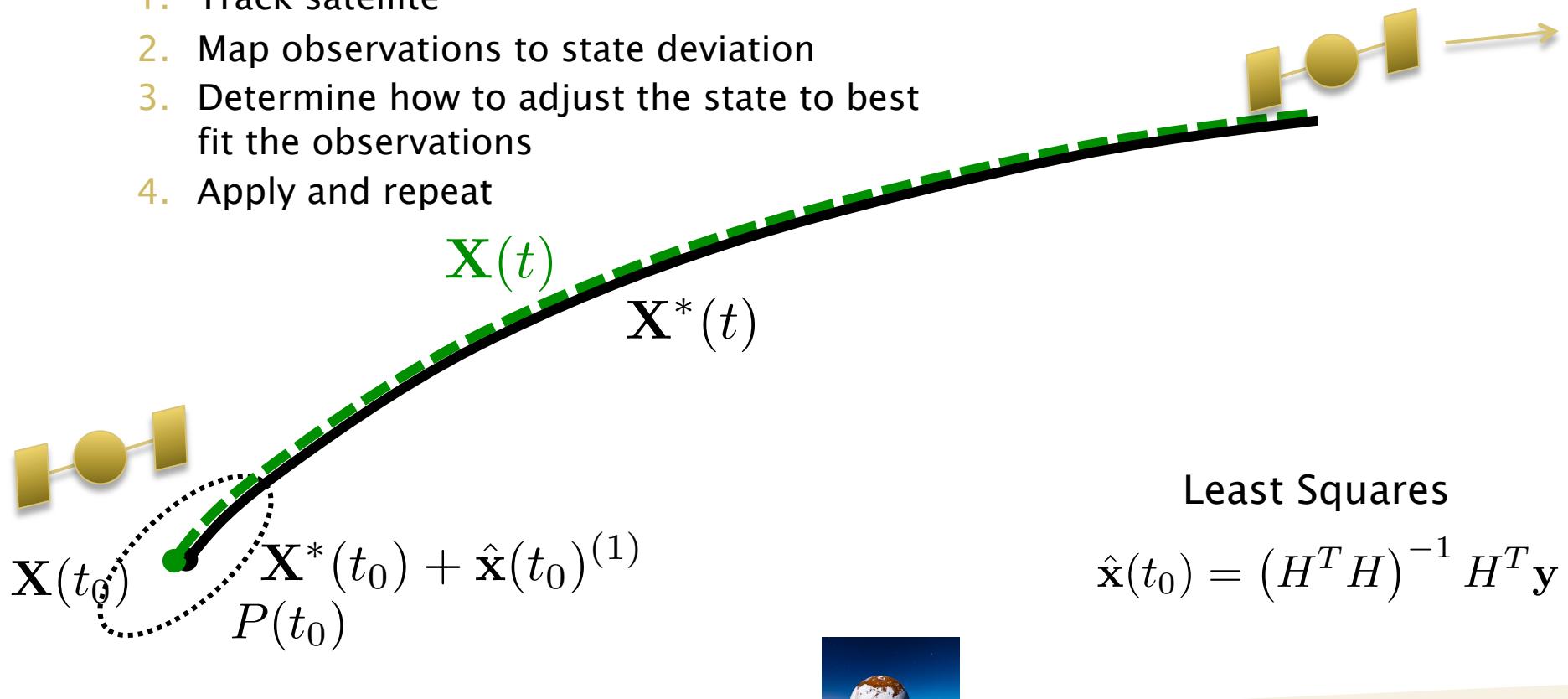
1. Track satellite
2. Map observations to state deviation
3. Determine how to adjust the state to best fit the observations



# Review of the Stat OD Process

## ▶ Process:

1. Track satellite
2. Map observations to state deviation
3. Determine how to adjust the state to best fit the observations
4. Apply and repeat

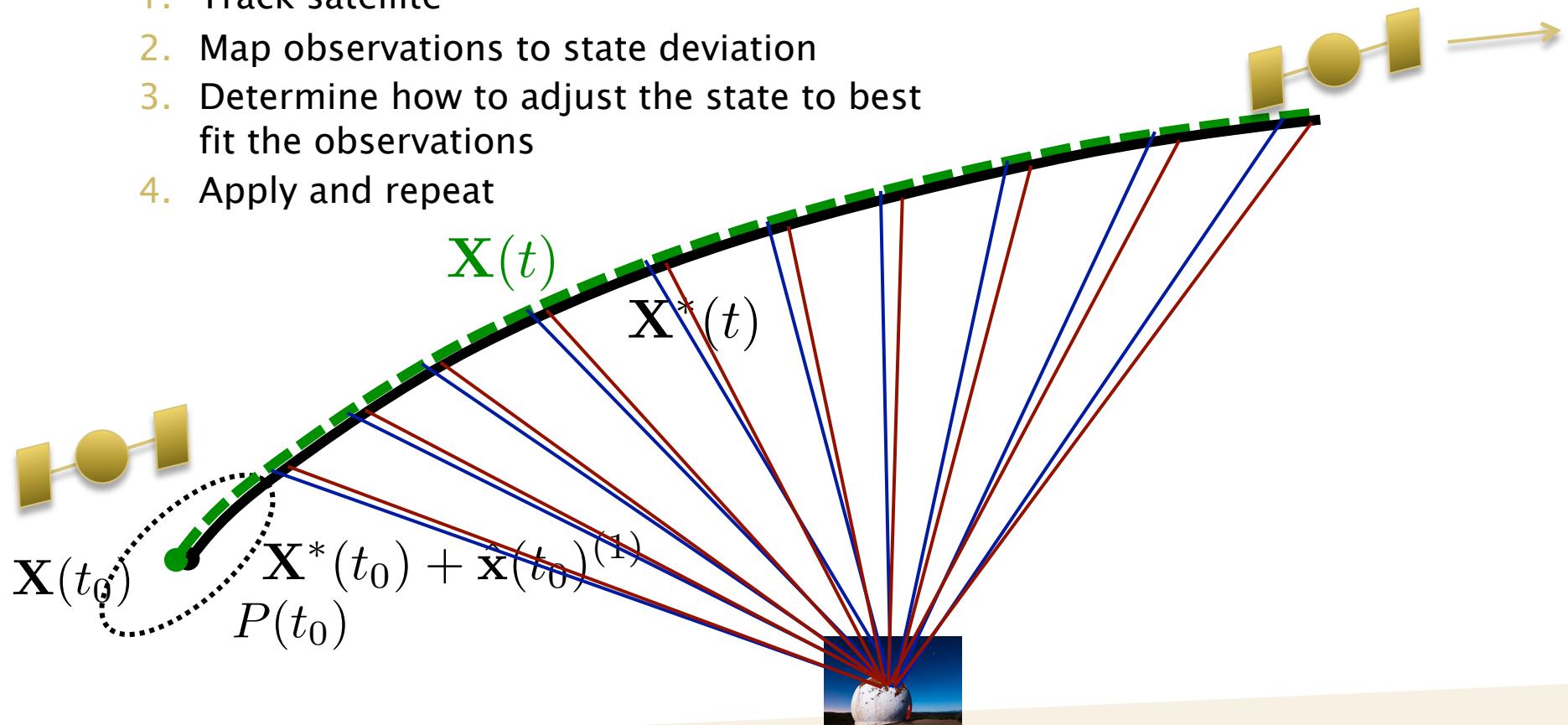


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# Review of the Stat OD Process

- ▶ Process:

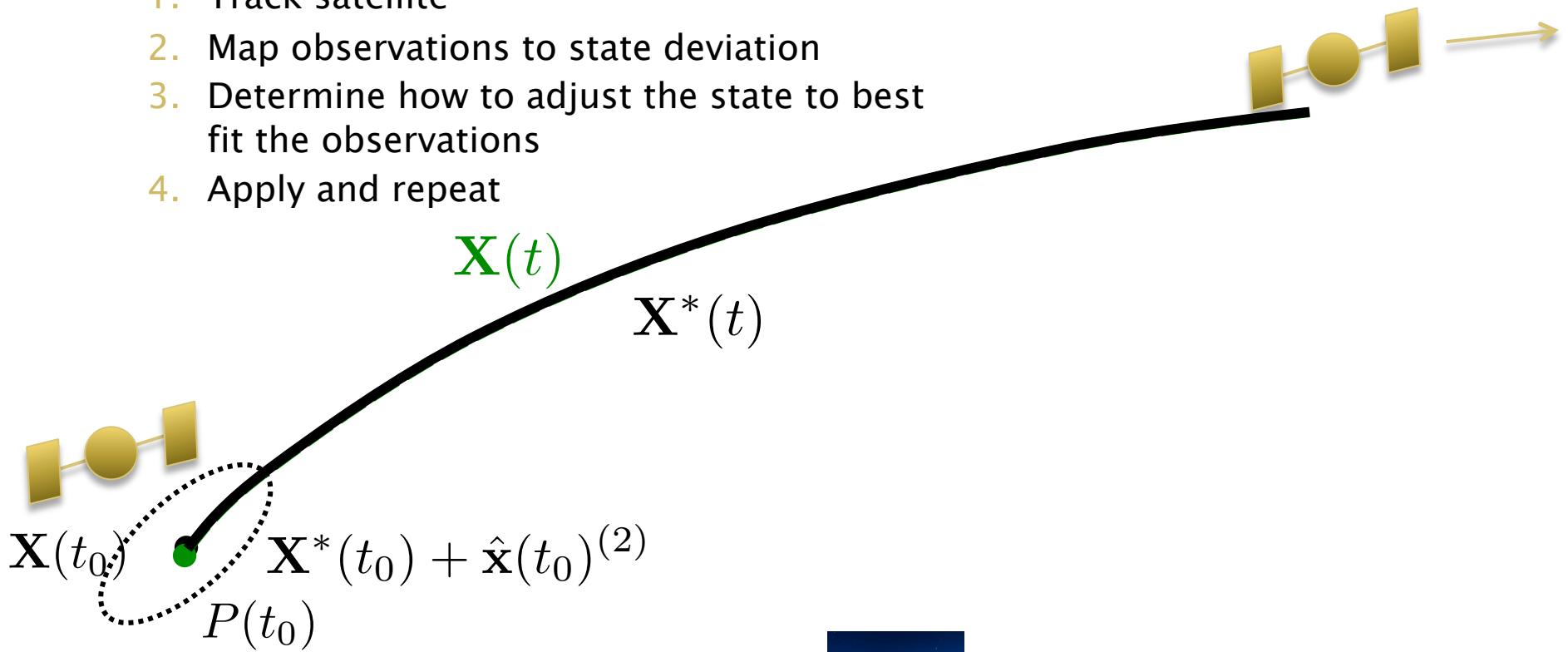
1. Track satellite
2. Map observations to state deviation
3. Determine how to adjust the state to best fit the observations
4. Apply and repeat



# Review of the Stat OD Process

## ▶ Process:

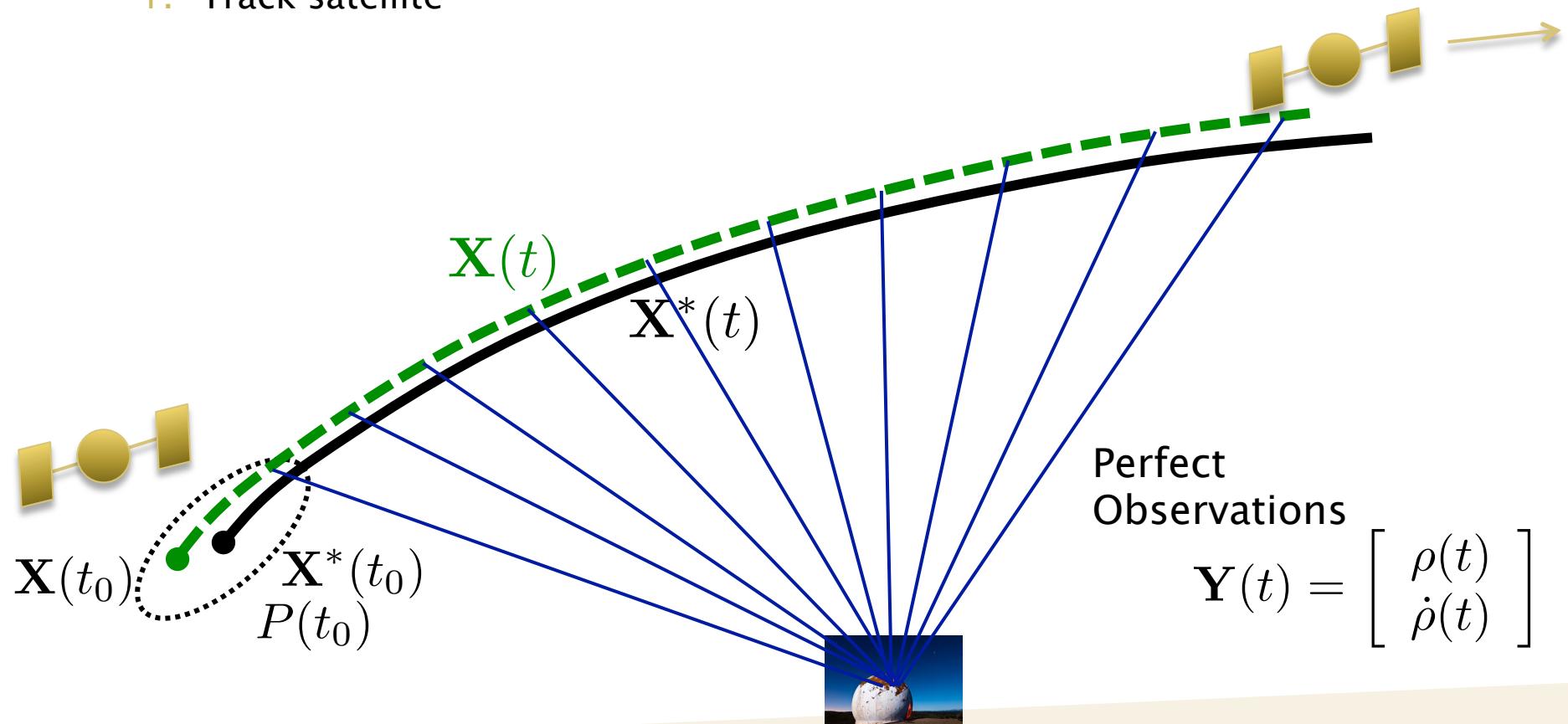
1. Track satellite
2. Map observations to state deviation
3. Determine how to adjust the state to best fit the observations
4. Apply and repeat



# Review of the Stat OD Process

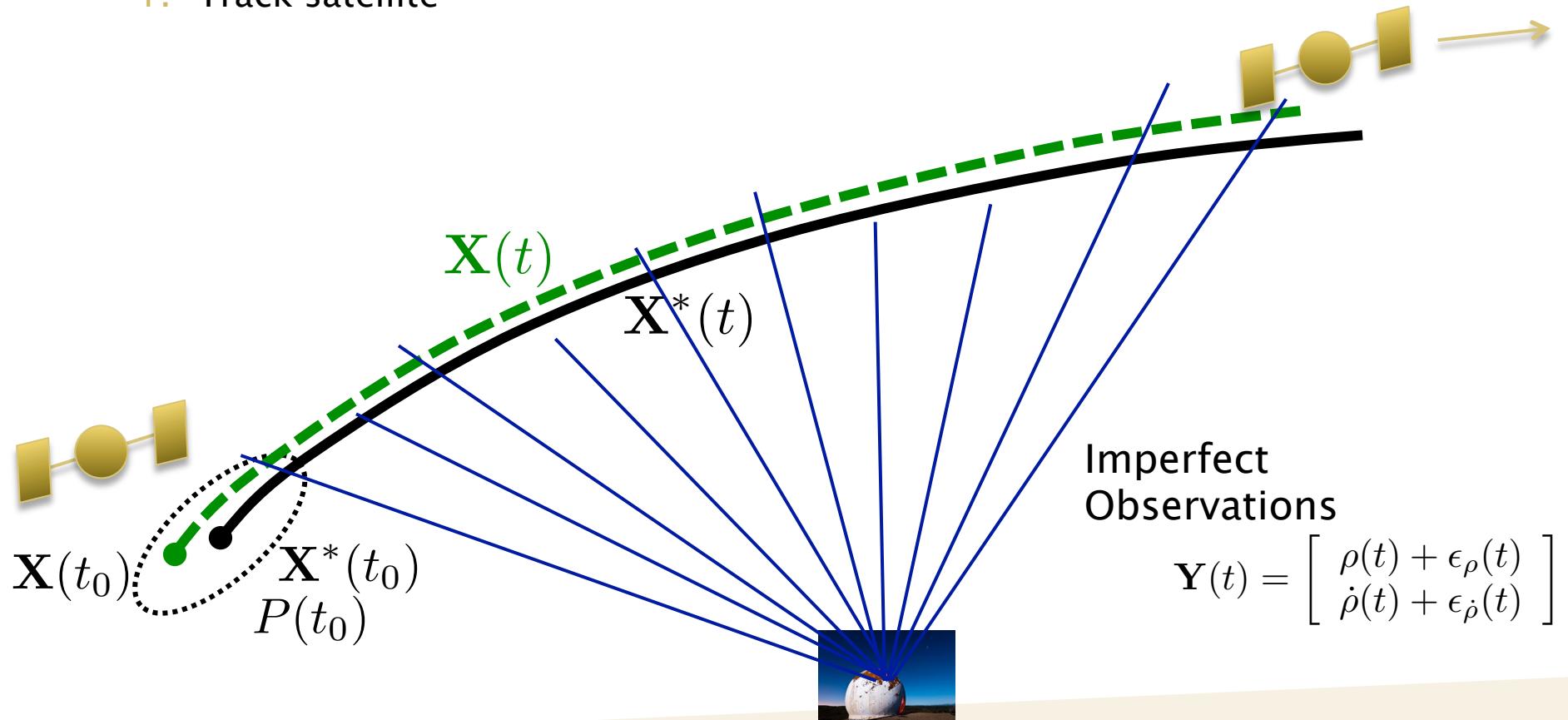
- ▶ Process:

1. Track satellite



# Review of the Stat OD Process

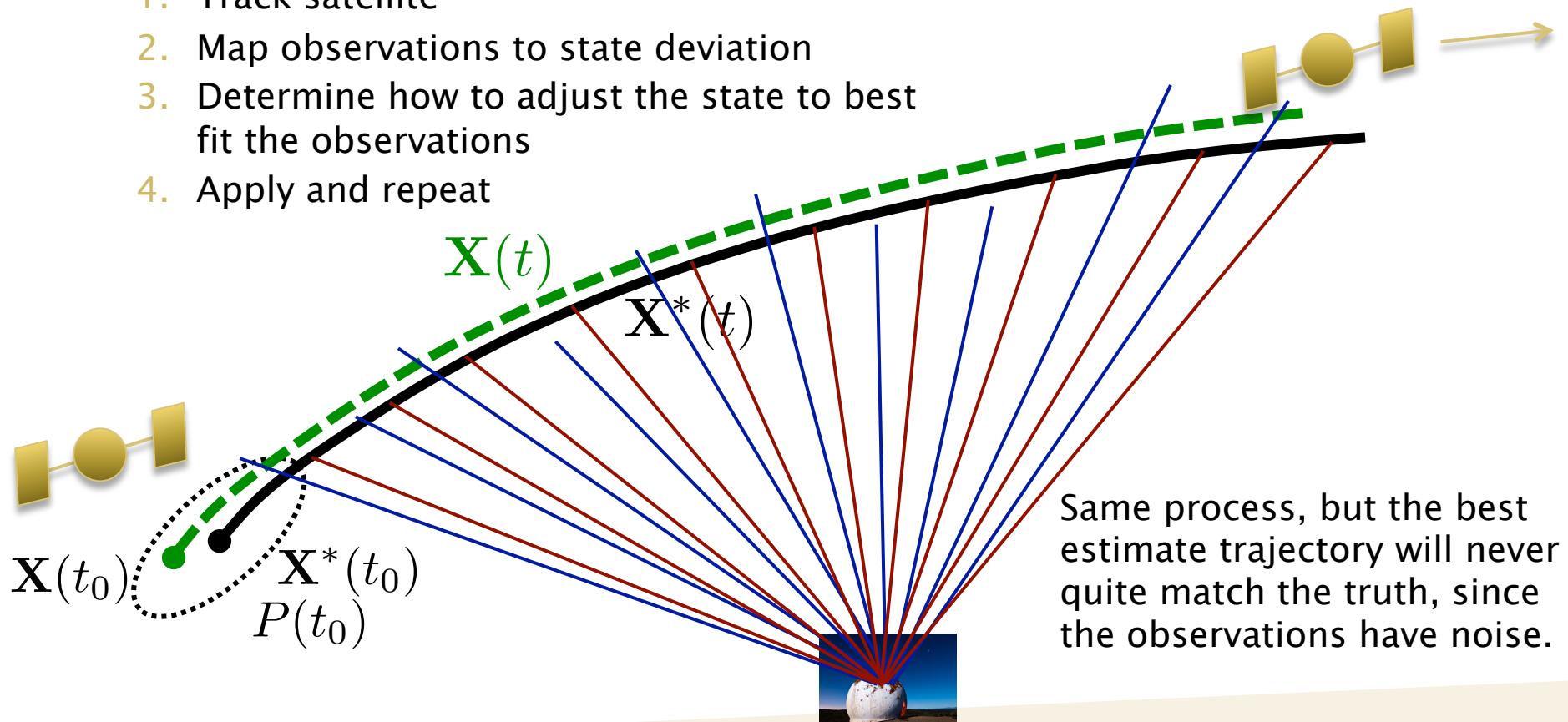
- ▶ Process:
  1. Track satellite



# Review of the Stat OD Process

## Process:

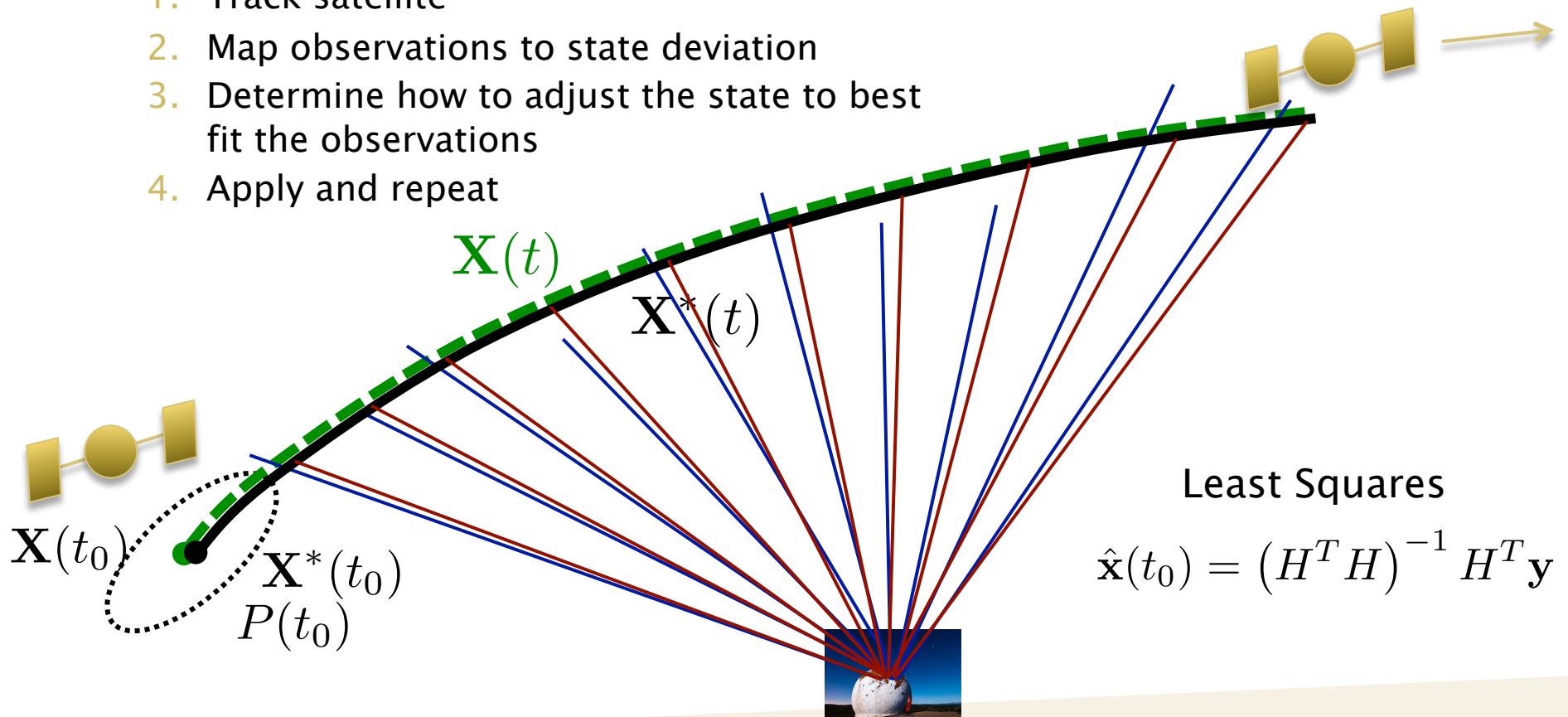
1. Track satellite
2. Map observations to state deviation
3. Determine how to adjust the state to best fit the observations
4. Apply and repeat



# Review of the Stat OD Process

## Process:

1. Track satellite
2. Map observations to state deviation
3. Determine how to adjust the state to best fit the observations
4. Apply and repeat



# Filter Options

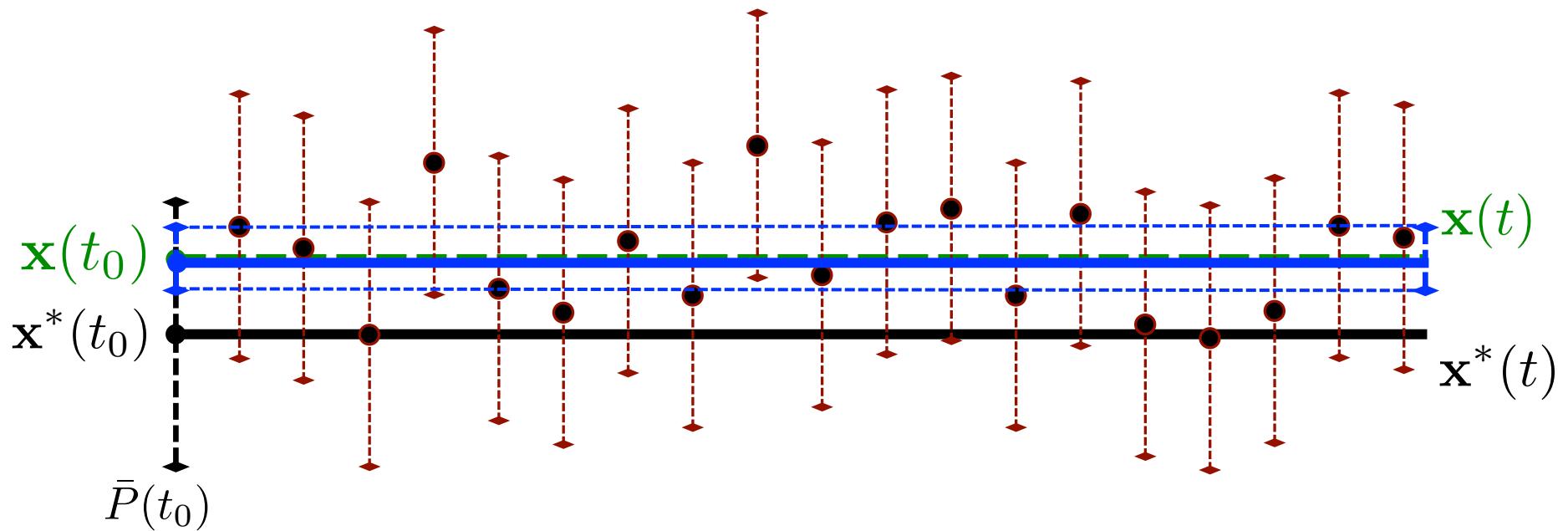
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- ▶ Batch
  - Using any of the Least-Squares derivations
- ▶ Sequential
  - CKF
  - EKF
  - UKF (others)



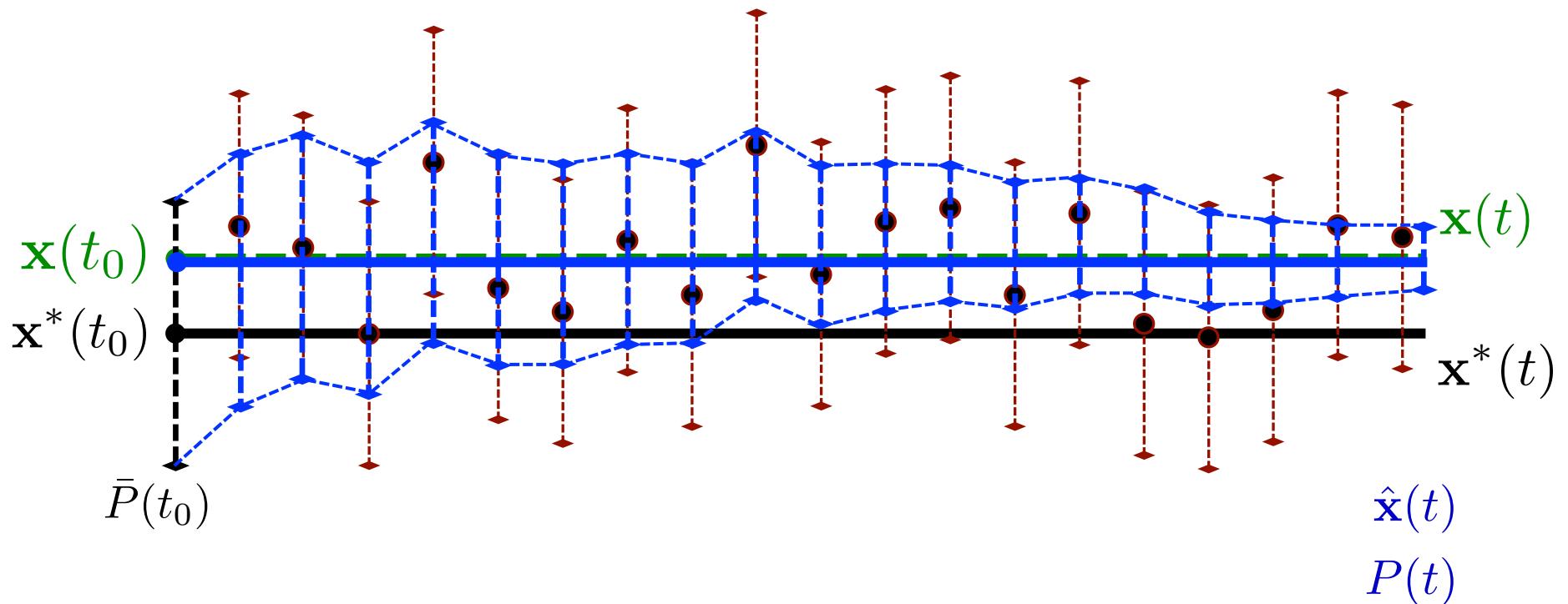
# Stat OD Conceptualization

## ► Least Squares (Batch)



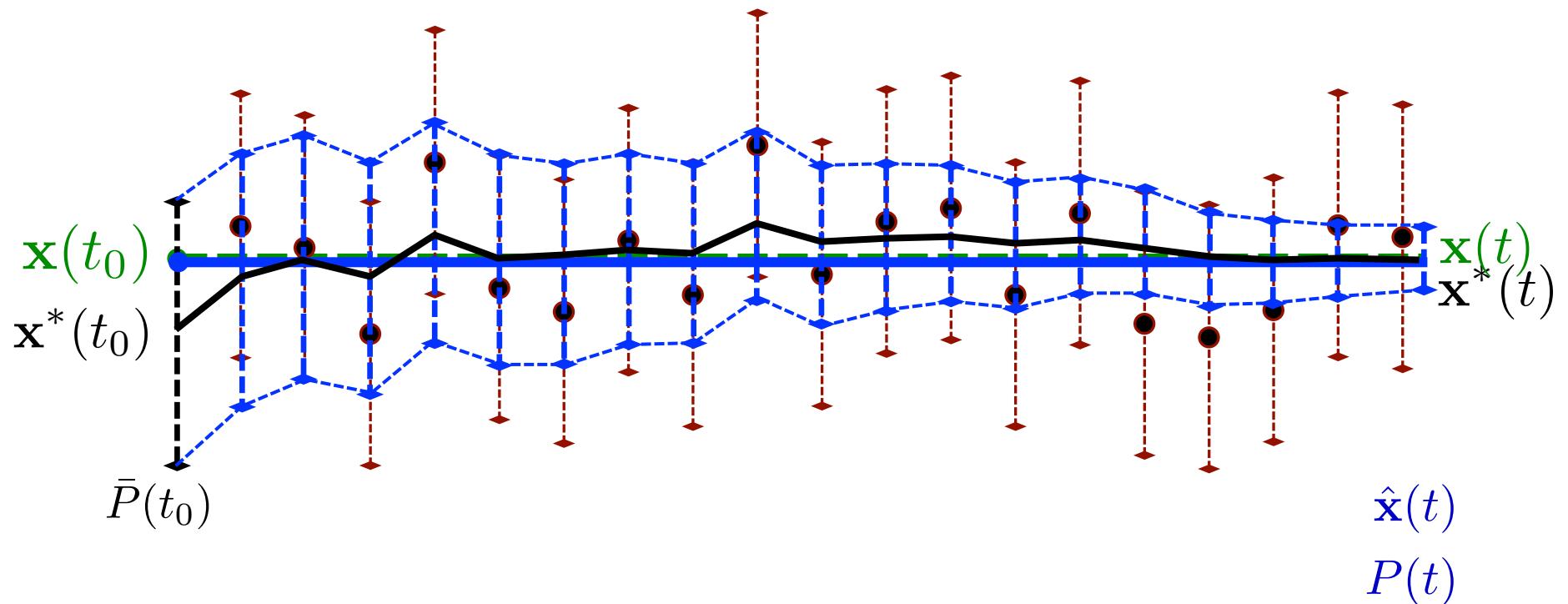
# Stat OD Conceptualization

## ► Conventional Kalman



# Stat OD Conceptualization

## ► EKF



# Numerical Issues

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- ▶ As we've seen, computers aren't perfect and Stat OD is a very sensitive subject!



# Joseph Formulation

- ▶ Replace

$$P_k = \left( I - K_k \tilde{H}_k^T \right) \bar{P}_k$$

with

$$P_k = \left( I - K_k \tilde{H}_k^T \right) \bar{P}_k \left( I - K_k \tilde{H}_k^T \right)^T + K_k R_k K_k^T$$

- ▶ This formulation will always retain a symmetric matrix, but it may still lose positive definiteness.



# Square Root Filter Algorithms

- ▶ Define  $W$ , the square root of  $P$ :

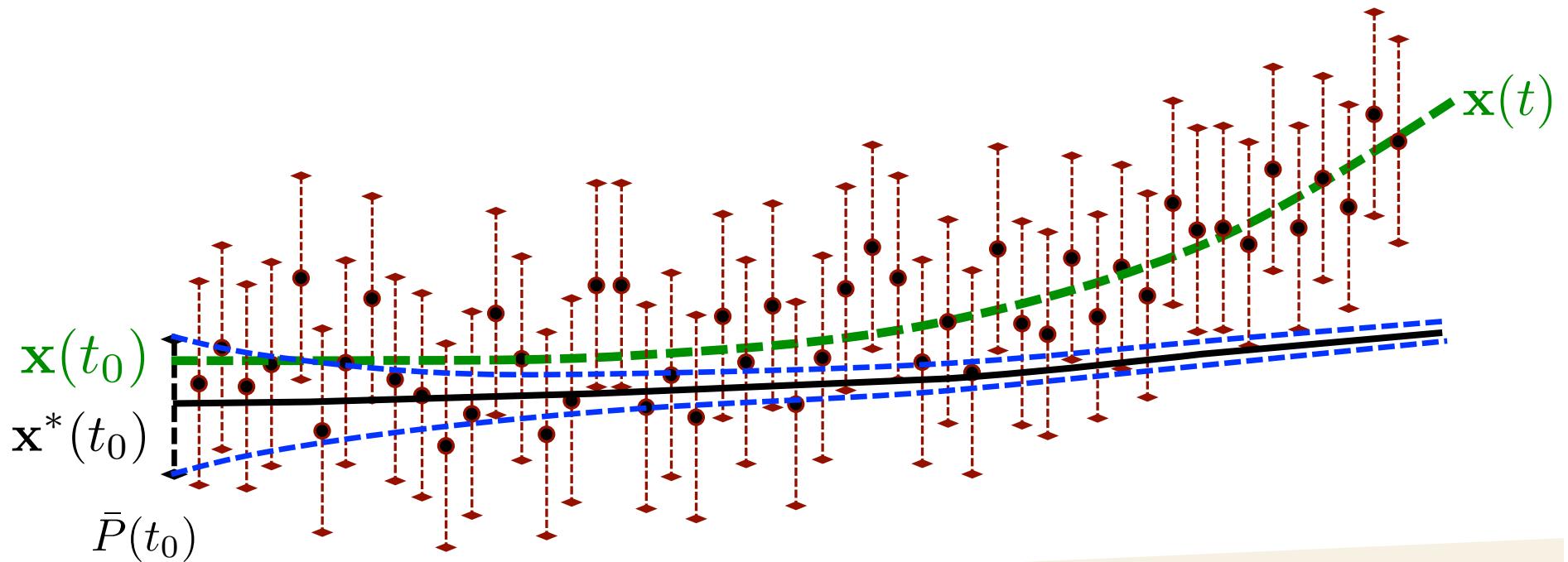
$$WW^T = P$$

- ▶ Observe that if we have  $W$ , then computing  $P$  in this manner will always result in a symmetric PD matrix.
- ▶ Perform measurement updates and time updates on  $W$  rather than  $P$ .
  - Often process one observation at a time (rather than a vector of observations).
- ▶  $W$  may be constructed via Givens, Householder, Cholesky, or other methods.



# Filter Saturation

- ▶ Applying the sequential algorithm to a large amount of data will cause the covariance to shrink down too far.



# Filter Saturation

- ▶ We need a way to add expected process noise to our filter.
- ▶ Many ways to do that:
  - State Noise Compensation
    - Constant noise
    - Piecewise constant noise
    - Correlated noise
    - White noise
  - Dynamic Model Compensation
    - 1<sup>st</sup> order linear stochastic noise
    - More complex model compensations



# Process Noise Time Update



- ▶ New time update:
- ▶ Old:  $\bar{P}_k = \Phi(t_k, t_{k-1}) P_{k-1} \Phi^T(t_k, t_{k-1})$
- ▶ New Time Update:  $\bar{P}_k = \Phi_{k,k-1} P_{k-1} \Phi_{k,k-1}^T + Q_\eta(t_k)$
- ▶ General:  $\bar{P}_k = \Phi_{k,k-1} P_{k-1} \Phi_{k,k-1}^T + \Gamma_{k,k-1} Q_k \Gamma_{k,k-1}^T$



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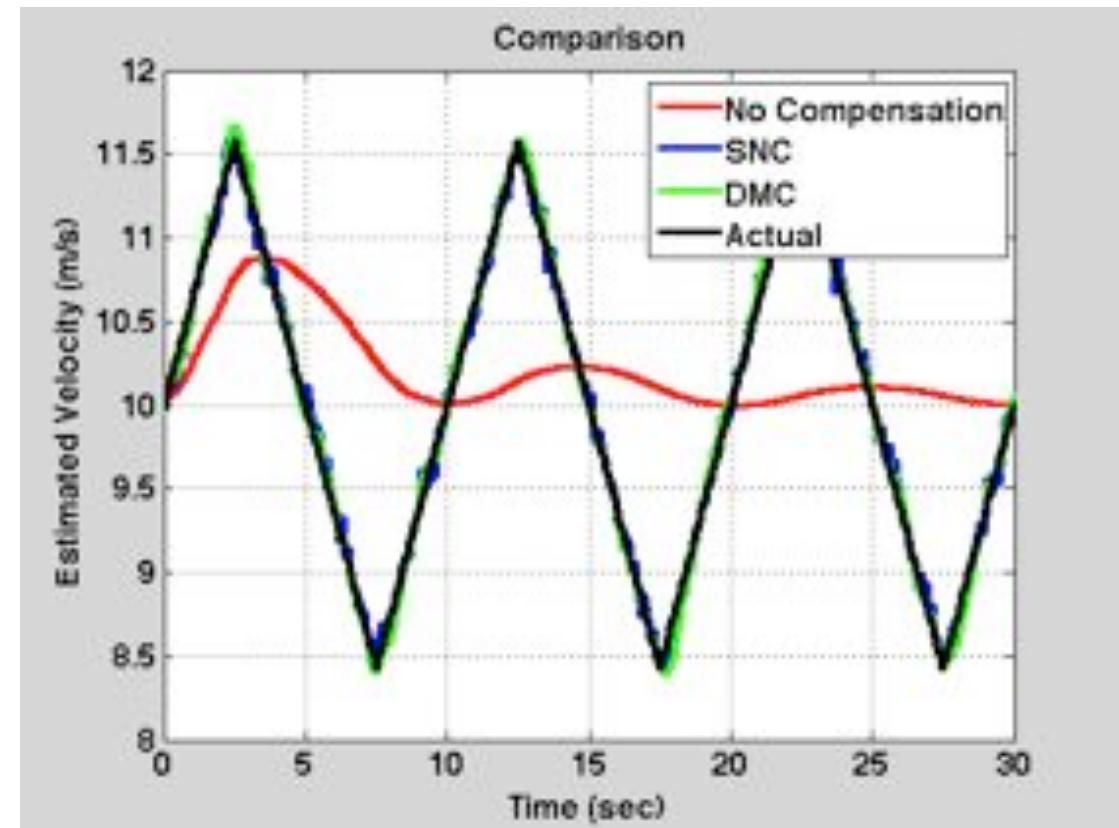
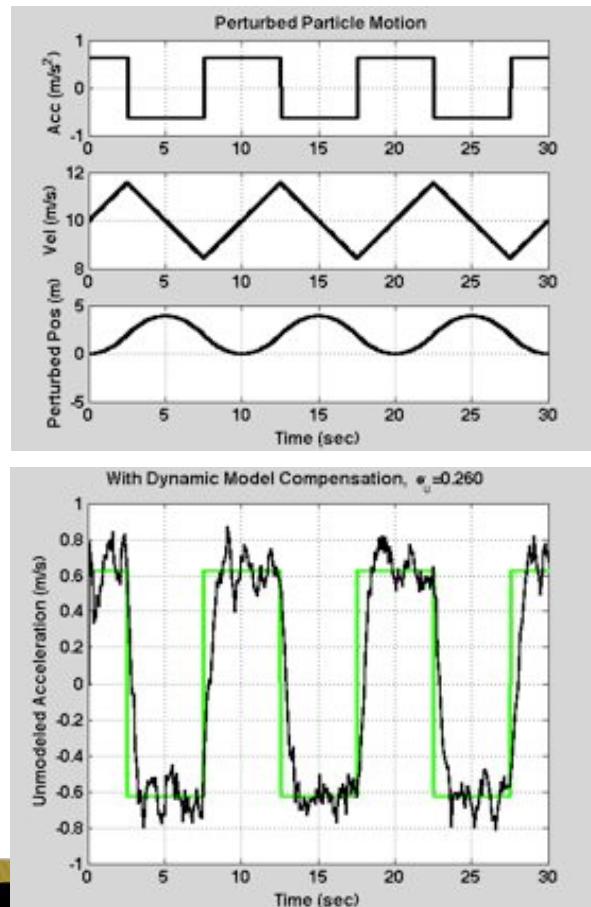
# Process Noise

- ▶ State Noise Compensation usually compensates for unmodeled dynamics by assuming it is some white noise process.
- ▶ Dynamic Model Compensation also estimates what the unmodeled acceleration is.
  - Adds a term or two to the state.



# Example SNC / DMC

## ► Square Wave unmodeled acceleration



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# Tuning the Filter

- ▶ To tune the filter:
- ▶ Practice on many simulated runs.
- ▶ Aim to tune the filter to add the least amount of inflation to the P-matrix while reducing the residuals to near-noise.
- ▶ Check the trace of the P-matrix. Is it too large?
- ▶ Do you know anything about the uncertainty in the model? Perhaps you can orient the Q matrix to accommodate for expected uncertainties (drag, SRP, maneuver errors, etc)



# Smoothing

- ▶ Estimate using process noise

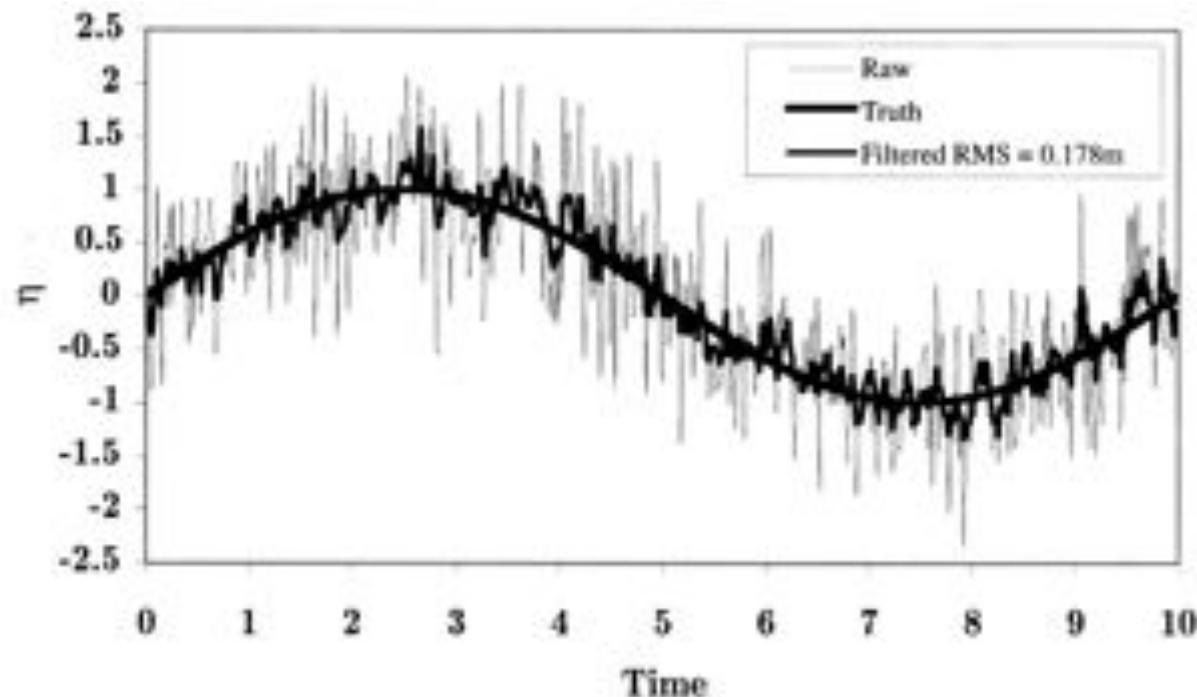


Figure 4.19.1: Process noise/sine wave recovery showing truth, raw data (truth plus noise) and the filtered solution.  $i_{j0} = 0$ ,  $\sigma = 2.49$ ,  $\beta = .045$ .



# Smoothing

## ► Smoothed estimate

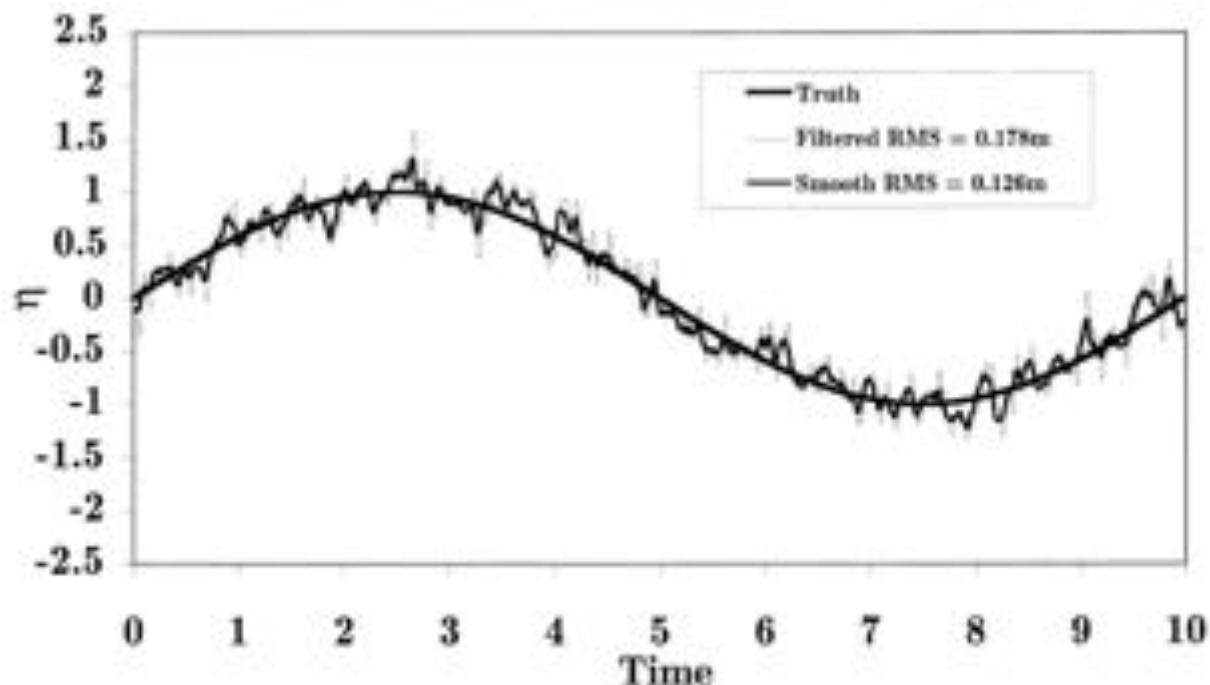


Figure 4.19.2: Process noise/sine wave recovery showing the truth, the filtered, and the smoothed solution.  $\bar{r}_0 = 0$ ,  $\sigma = 2.49$ ,  $\beta = .045$ .



# Using Information

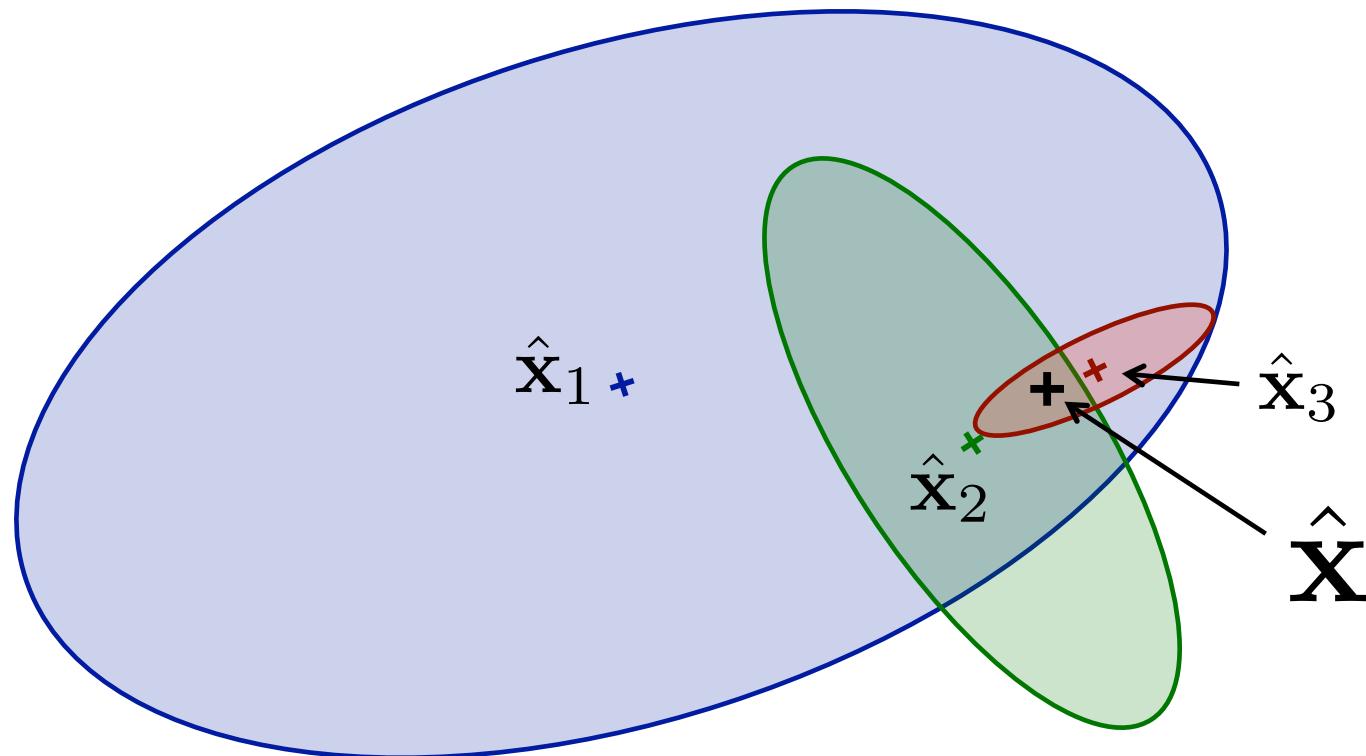
- ▶ We may be interested in comparing solutions that were generated using a variety of sources.
  - Not all of these solutions will be independent!
- ▶ If you have multiple solutions that *are* independent and uncorrelated, then we can combine them to make a *best* estimate.

$$\hat{\mathbf{x}} = \left( \sum_{i=1}^n P_i^{-1} \right)^{-1} \sum_{i=1}^n P_i^{-1} \hat{\mathbf{x}}_i$$



# Combining Estimates

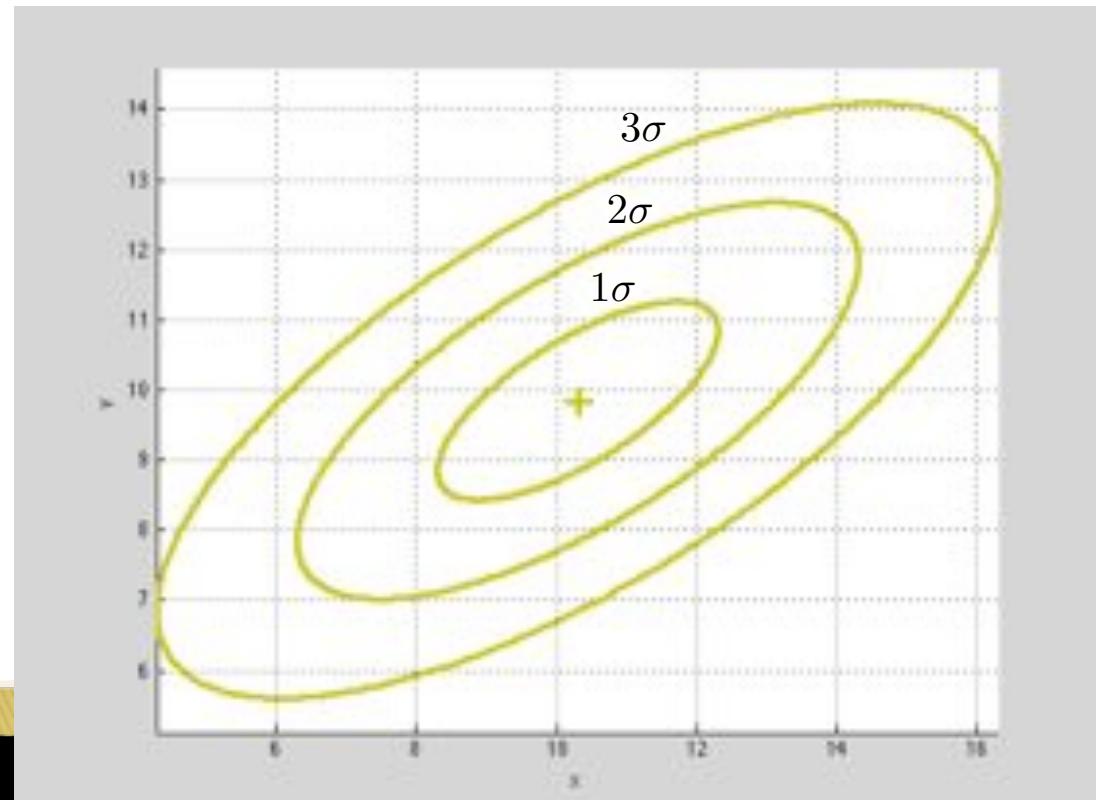
- Where would the optimal estimate lie given these estimates and associated errors covariances?



# Covariance → Probability Ellipsoid

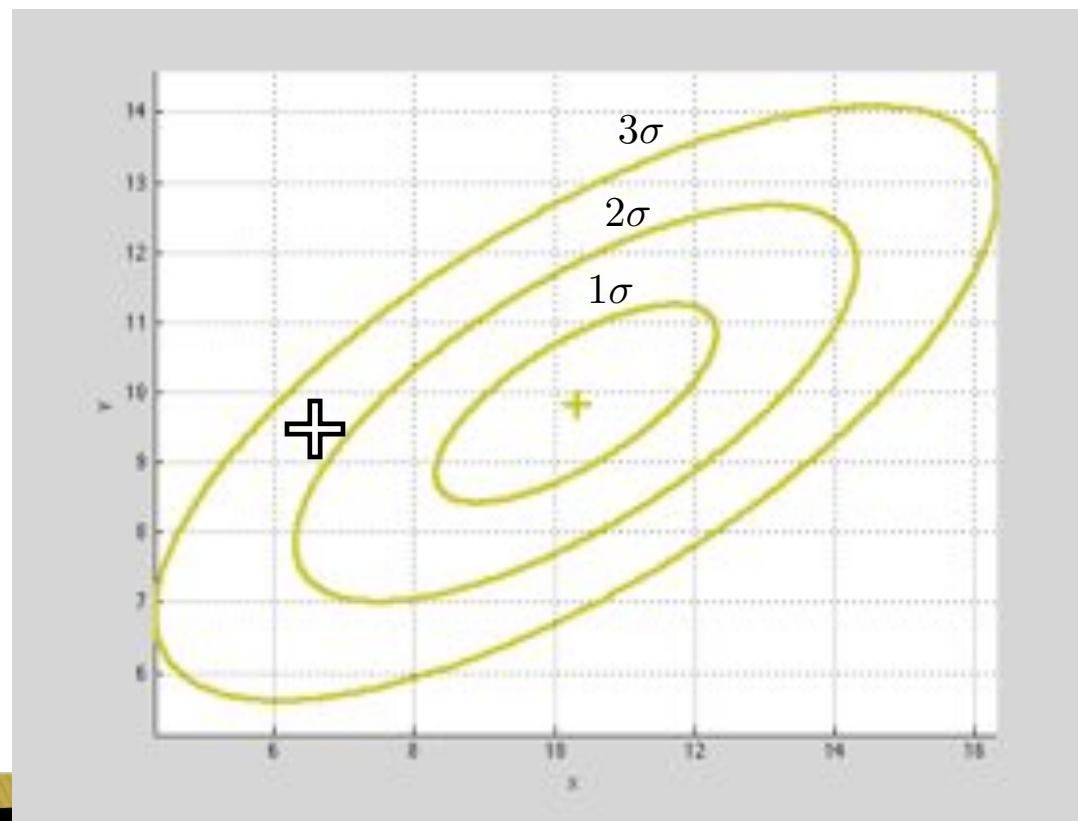
- ▶ Demonstrated how to convert a covariance matrix into a probability ellipsoid.
  - Plot it as an ellipse onto your design space
  - E.g., B-Plane
- ▶ Example:

$$P = \begin{bmatrix} 4 & 2 \\ 2 & 2 \end{bmatrix}$$



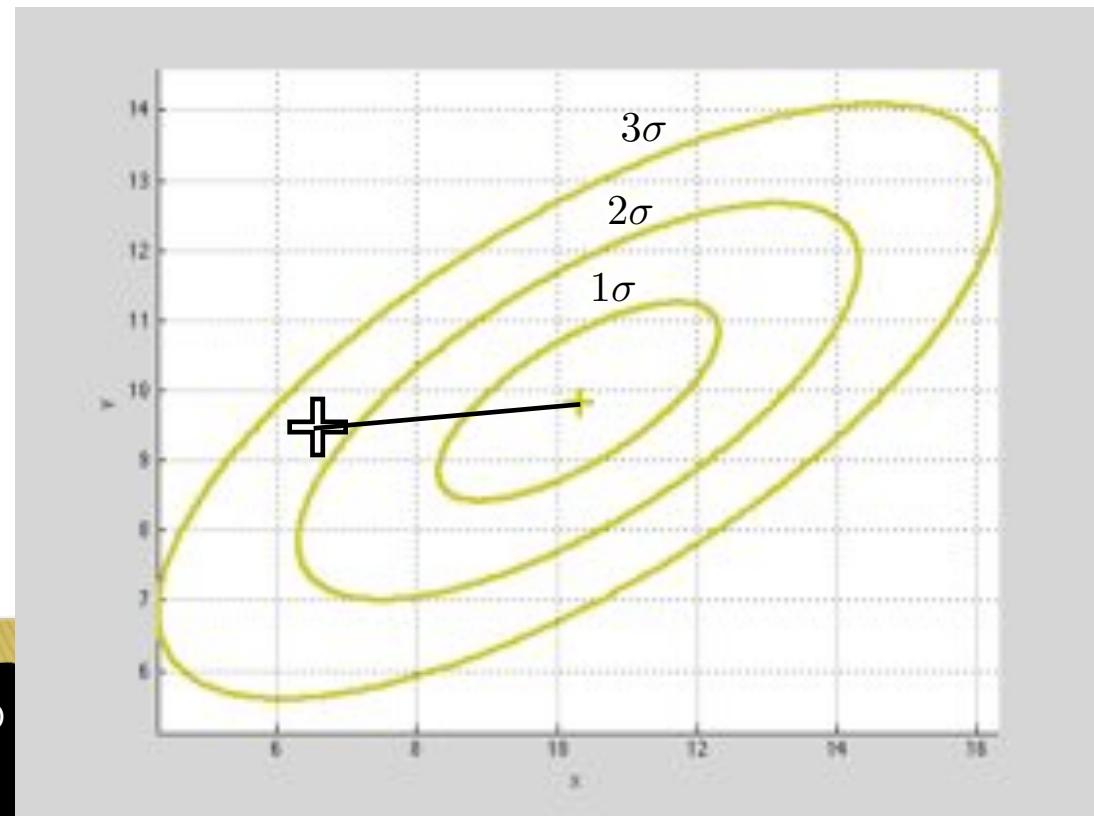
# Covariance → Probability Ellipsoid

- ▶ Question: how many sigmas is this example point away from the mean?



# Covariance → Probability Ellipsoid

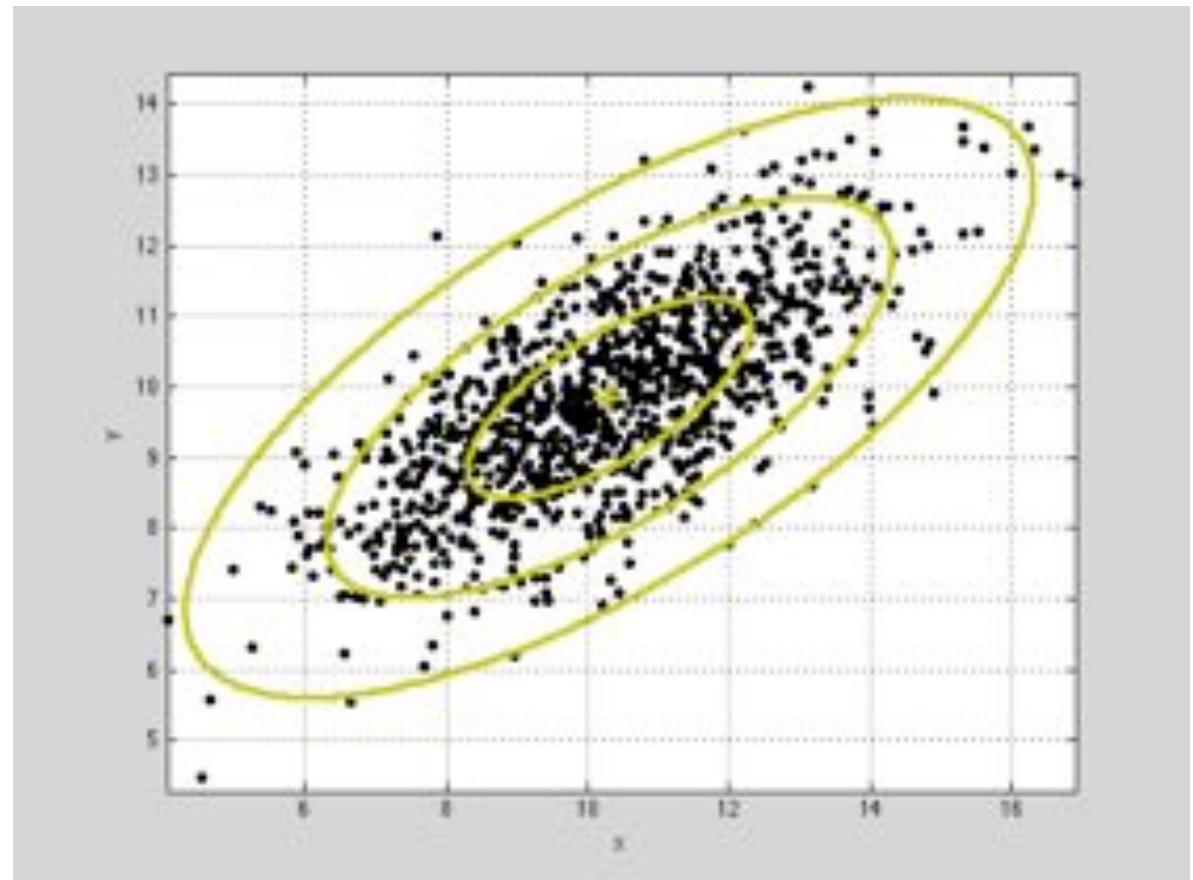
- ▶ Answer: ~2.4
- ▶ Rotate the point into the principal axes, then scale its new  $x'$  and  $y'$  values by the semi-axes and compute the distance to the mean.
- ▶  $N\sigma = \sqrt{(x'/a)^2 + (y'/b)^2}$



# Monte Carlo

- ▶ Use Monte Carlo to sample a covariance.

- $S = \text{chol}(P)$
- $\text{for } i=1:1000$ 
  - $e = \text{randn}(n,1)$
  - $x = S^*e$
- $\text{end}$



# Spaceflight Operations

- ▶ I wanted to finish Stat OD by talking about Spaceflight operations in practice.
- ▶ Interplanetary and Earth orbiting



# Flight Operations

## ► Good practices in spaceflight navigation

- Practice! Tune your filter on all kinds of data. Be ready for a wide variety of data.
- Perform lots of solutions and compare them.
  - Solutions over different arcs of time, long and short
  - Solutions with different data types
  - Solutions with different parameters, consider parameters, process noise, etc.
- Present the information in a manager-friendly format, but understand the details.
  - B-Plane, error ellipses, covariance, residuals
- Look at that covariance in different ways.
- Don't neglect the numerical details.



# Missions that require navigation

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- ▶ All of them.



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# Spacecraft missions

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- ▶ All spacecraft require OD
  - For communication
- ▶ Most spacecraft require OD for other reasons
  - For science
  - For mission planning
  - For maneuver design



# The State Parameters

- ▶ Typical spacecraft solutions include the following parameters:
  - Position of the spacecraft
  - Velocity of the spacecraft
  - Attitude of the spacecraft
    - At discrete moments, or a time history
  - Maneuver components
    - As complicated as needed to model the maneuvers well, including:
    - Right ascension and declination of thrust vector
    - Pointing time-series
    - Thrust time-series
    - Mass-flow time-series
  - Small forces
    - ACS, desats, venting, etc.
  - Solar Pressure: bias, stochastic
  - Range biases to each ground station, per pass
  - Gravity field of target body, as applicable
  - Miscellaneous parameters that describe any modeled acceleration on the spacecraft.

Only non-spacecraft  
parameters in a typical  
state!



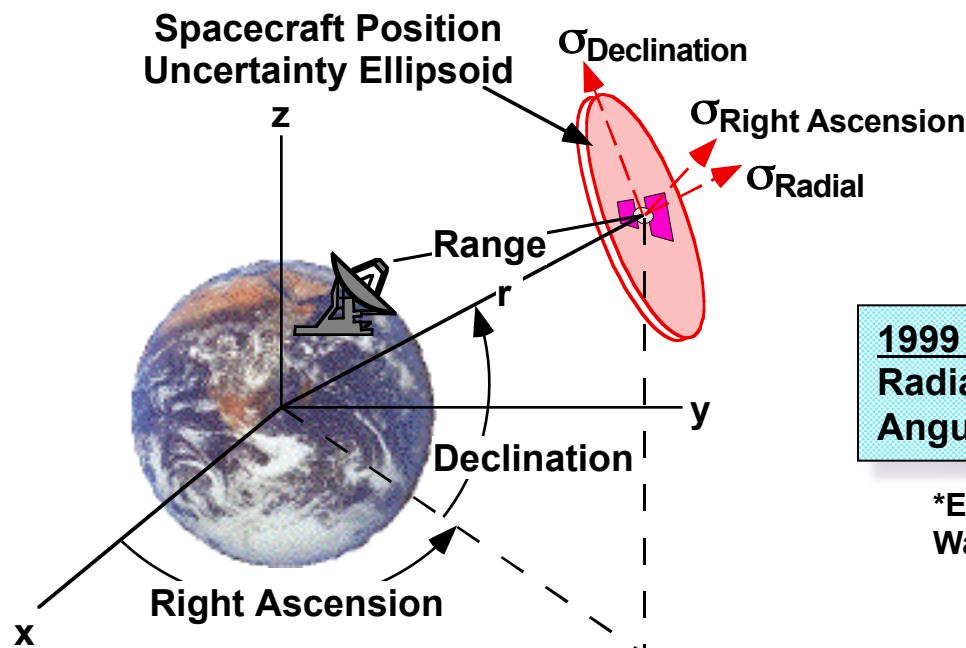
# Tracking Data

- ▶ Tracking data may include many types of data – and often *should* include many types of data:
  - Ground observations:
    - Doppler
    - Range
    - 1-Way, 2-Way, 3-Way
    - Angles when very near the Earth
    - Delta-DOR when further from Earth
  - Relative to other spacecraft, vehicles, bodies
    - GPS
    - Autonav
    - LiAISON
    - Formation Flying
  - Spacecraft measurements:
    - Accelerations, including drag-free corrections, thrust, etc.
    - Measured mass-flow
    - Attitude measurements



# Radial vs. Angular Measurements

- For most interplanetary missions, S/C position uncertainty is much smaller in Earth-spacecraft (“radial”) direction than in any angular (“plane-of-sky”) direction



1999 Capability	Position	Velocity
Radial Error	2 m	0.1 mm/s
Angular Error (at 1 AU)	3 km*	0.1 m/s

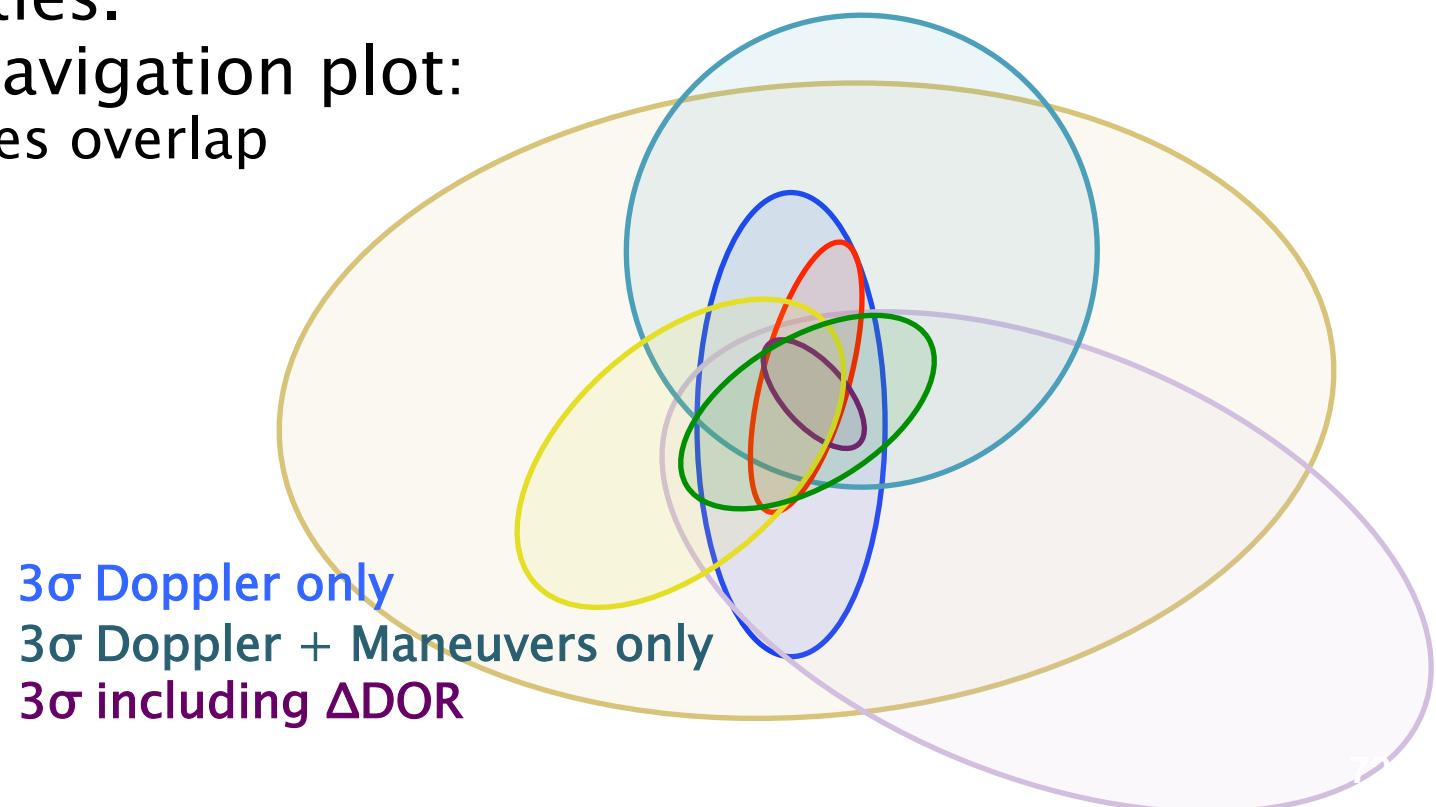
\*Equivalent to angle subtended by quarter atop Washington Monument as viewed from Chicago



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# Different Solutions

- ▶ Solutions are generated using numerous combinations of data types.
- ▶ This works to prevent another “unit-conversion” problem, as well as measurement corruption issues such as issues with singularities.
- ▶ A good navigation plot:
  - All ellipses overlap

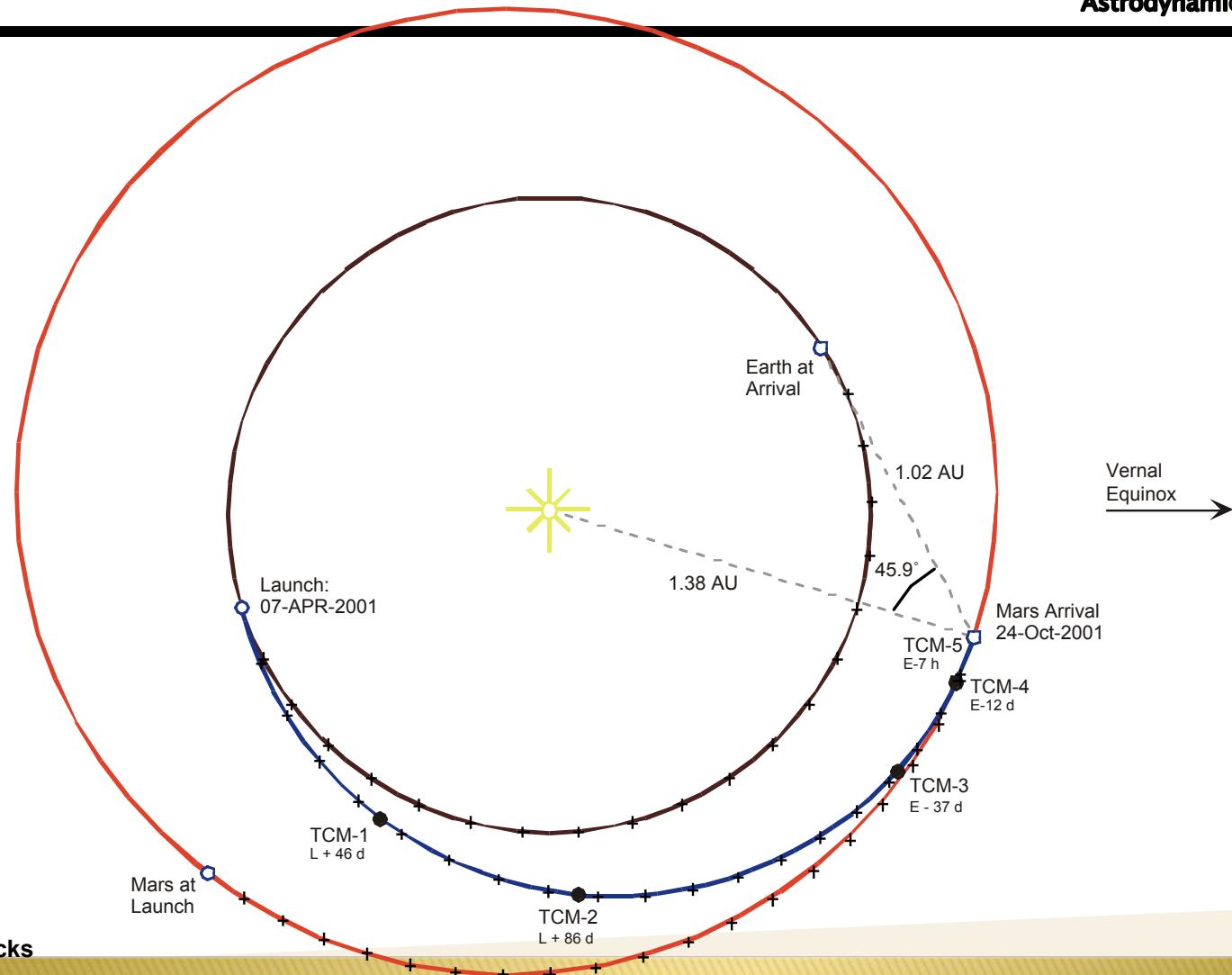


# Spacecraft missions

- ▶ We presented a few practical examples
  - Mars Odyssey
  - Cassini navigating through a Titan flyby
  - Chandrayaan-1
  - Of course plenty of GRAIL references

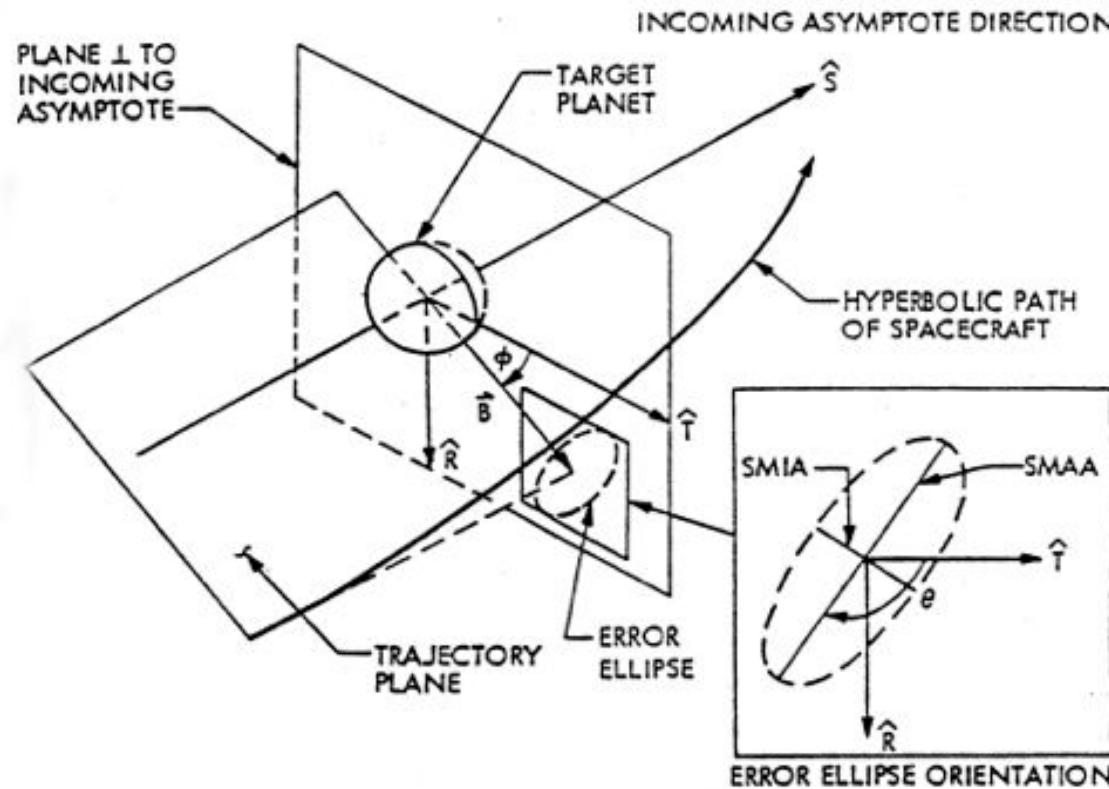


# Mars Odyssey Interplanetary Trajectory

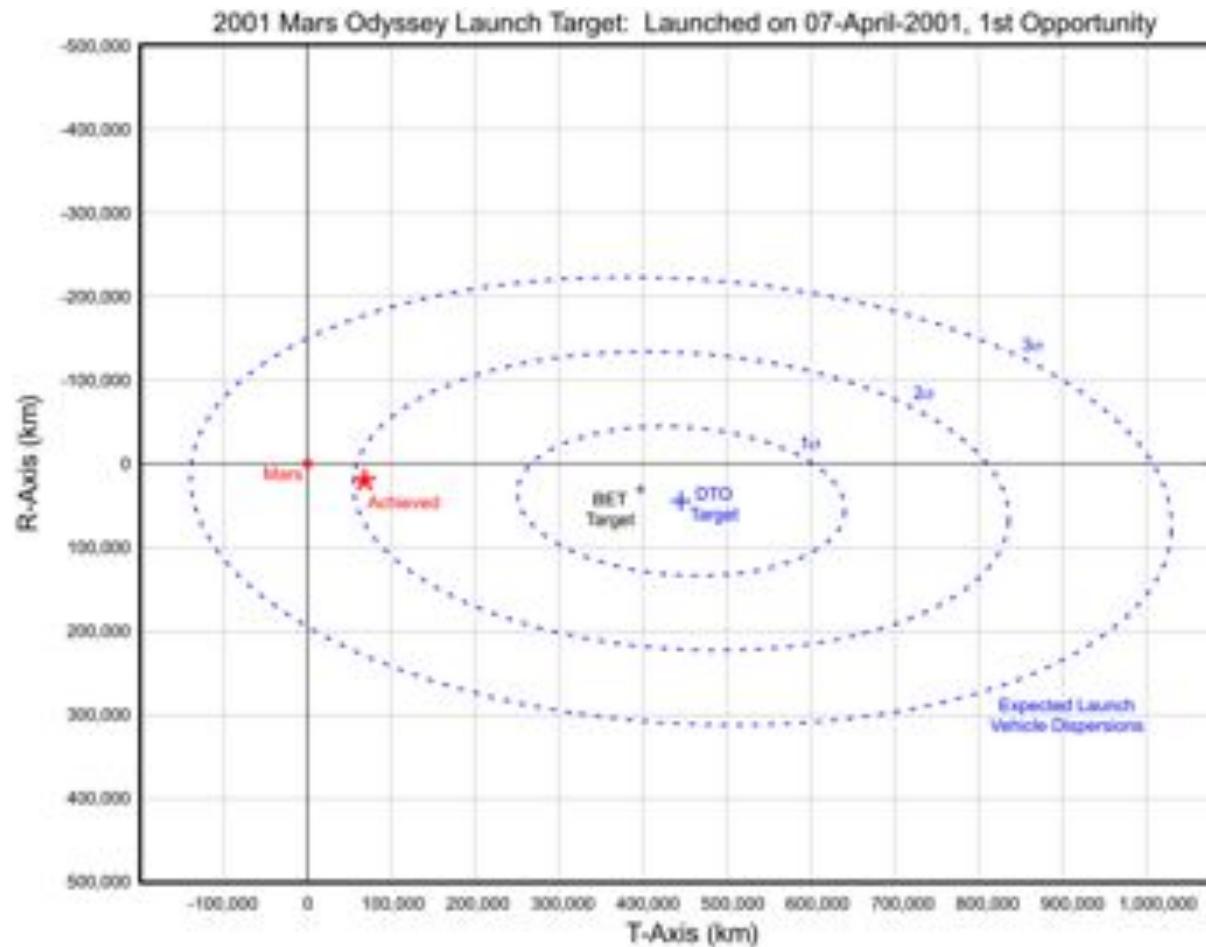


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# The B-plane



# Mars Odyssey Navigation



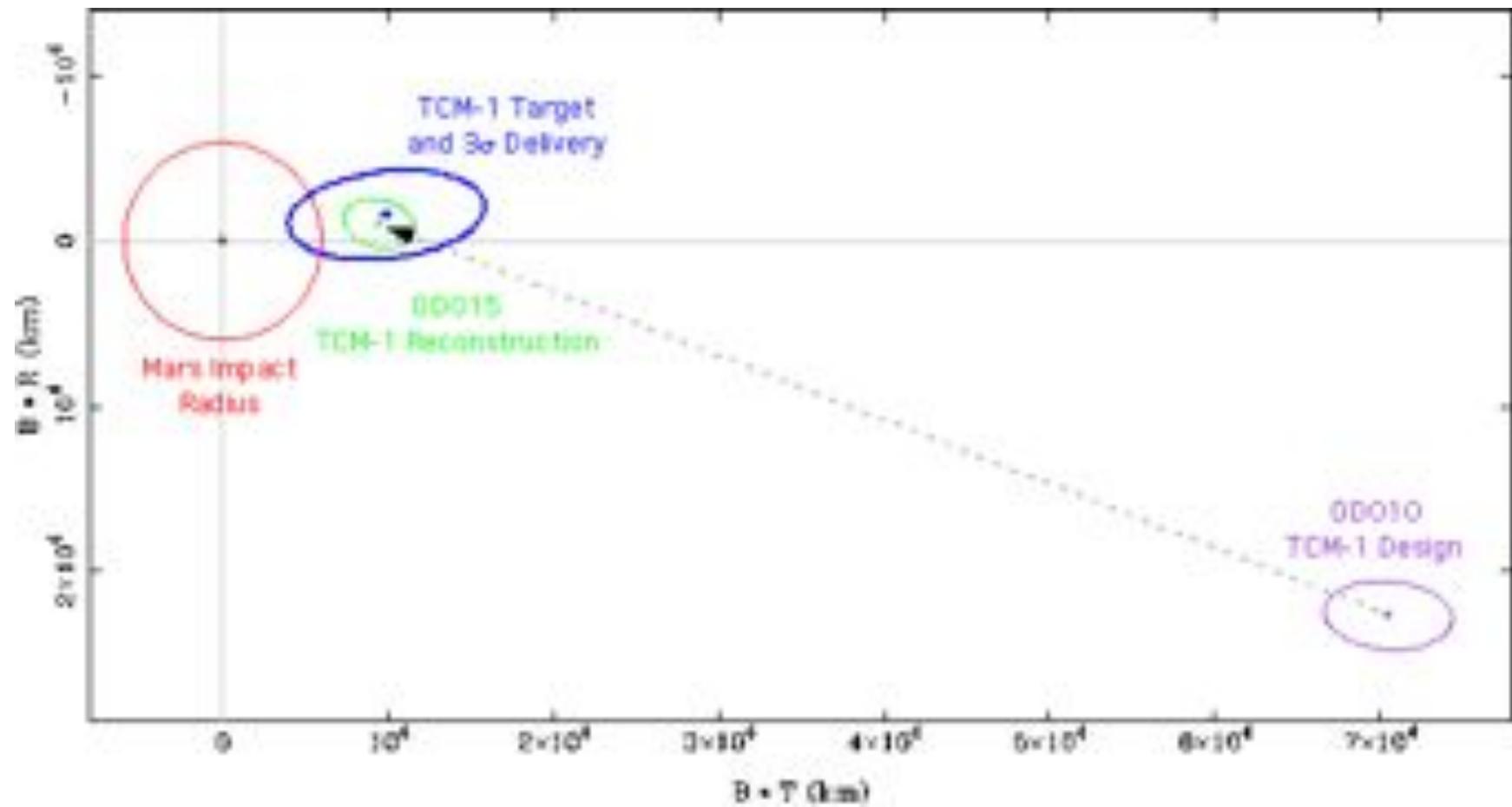
FAM 4/13/01



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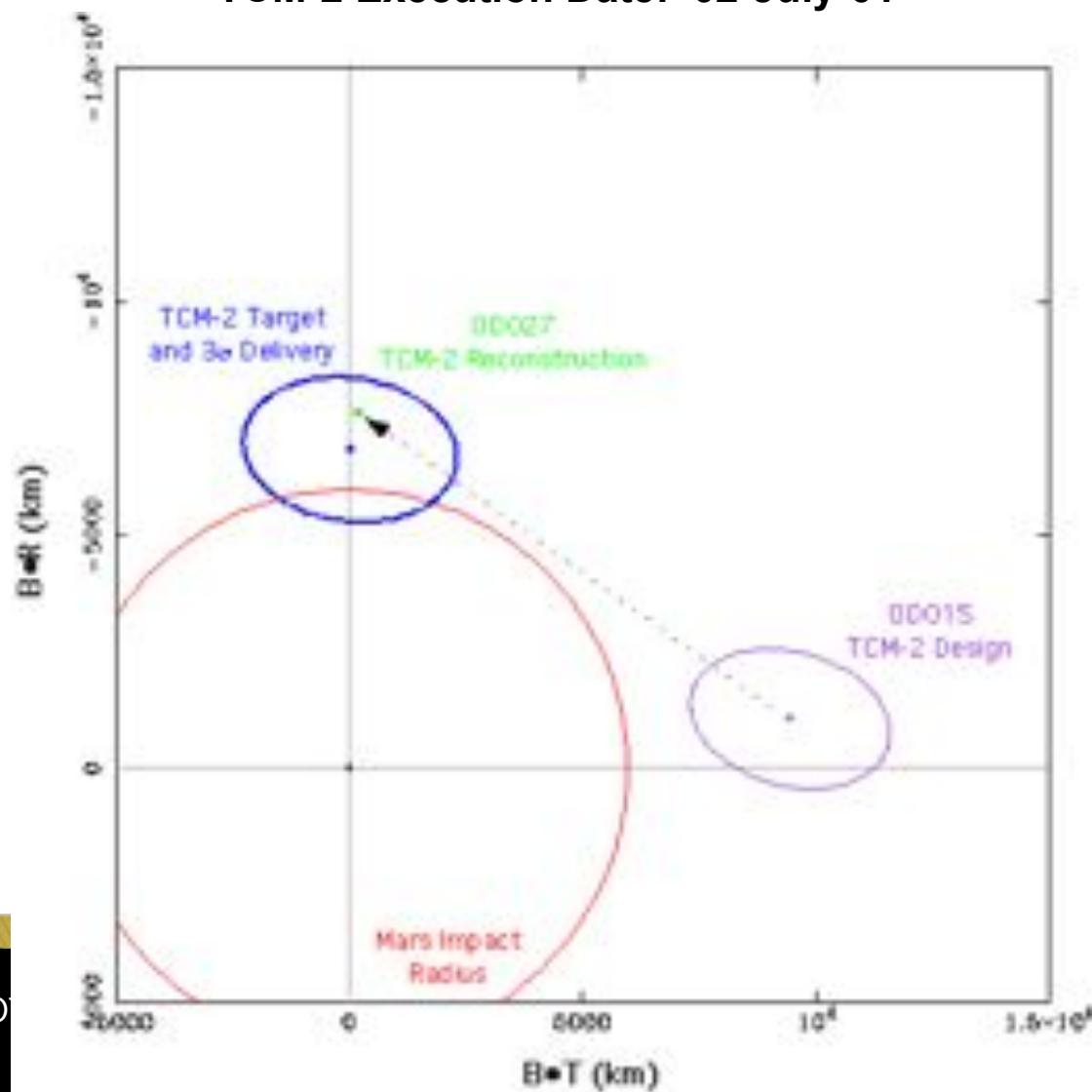
# Mars Odyssey Navigation

TCM-1 Execution Date: 23-May-01



# Mars Odyssey Navigation

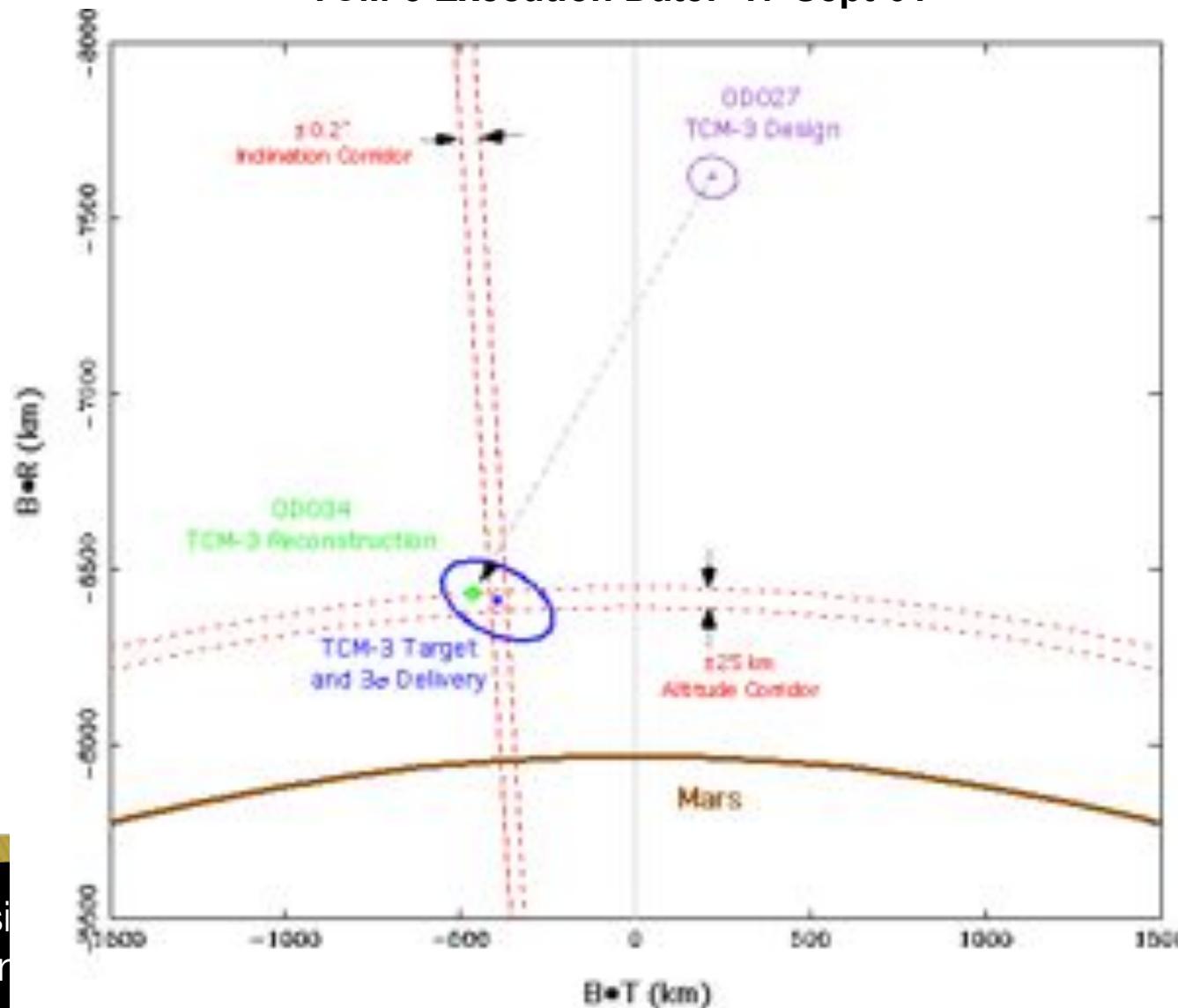
TCM-2 Execution Date: 02-July-01



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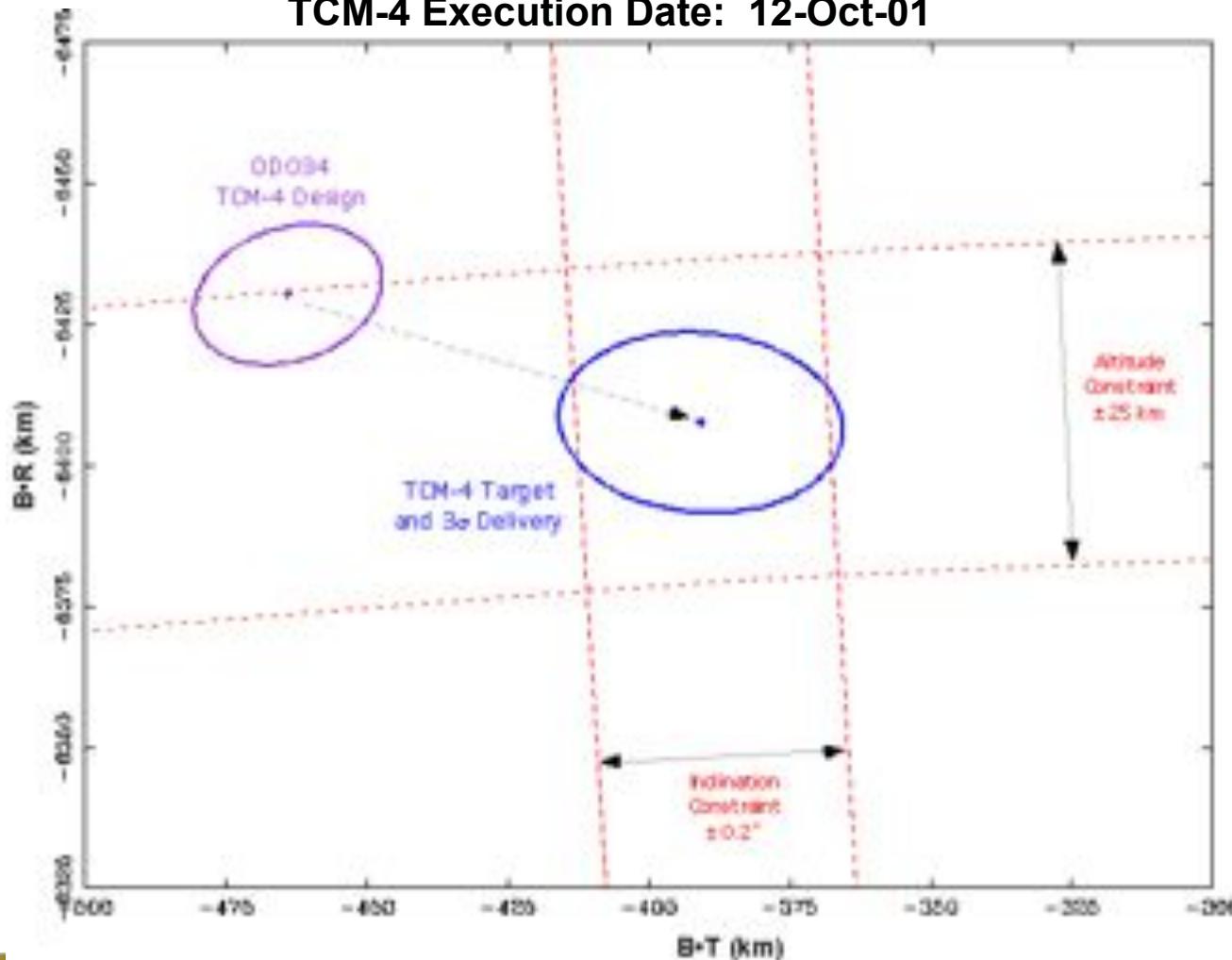
# Mars Odyssey Navigation

TCM-3 Execution Date: 17-Sept-01



# Mars Odyssey Navigation

TCM-4 Execution Date: 12-Oct-01



### Target

Alt: 300 km  
Inc: 93.47 °

### Current Estimate (OD034)

Alt: 324.1±11 km  
Inc: 94.10°±0.2°

### Current Miss (Est-Target)

Alt: +24 km  
Inc: +0.6 °

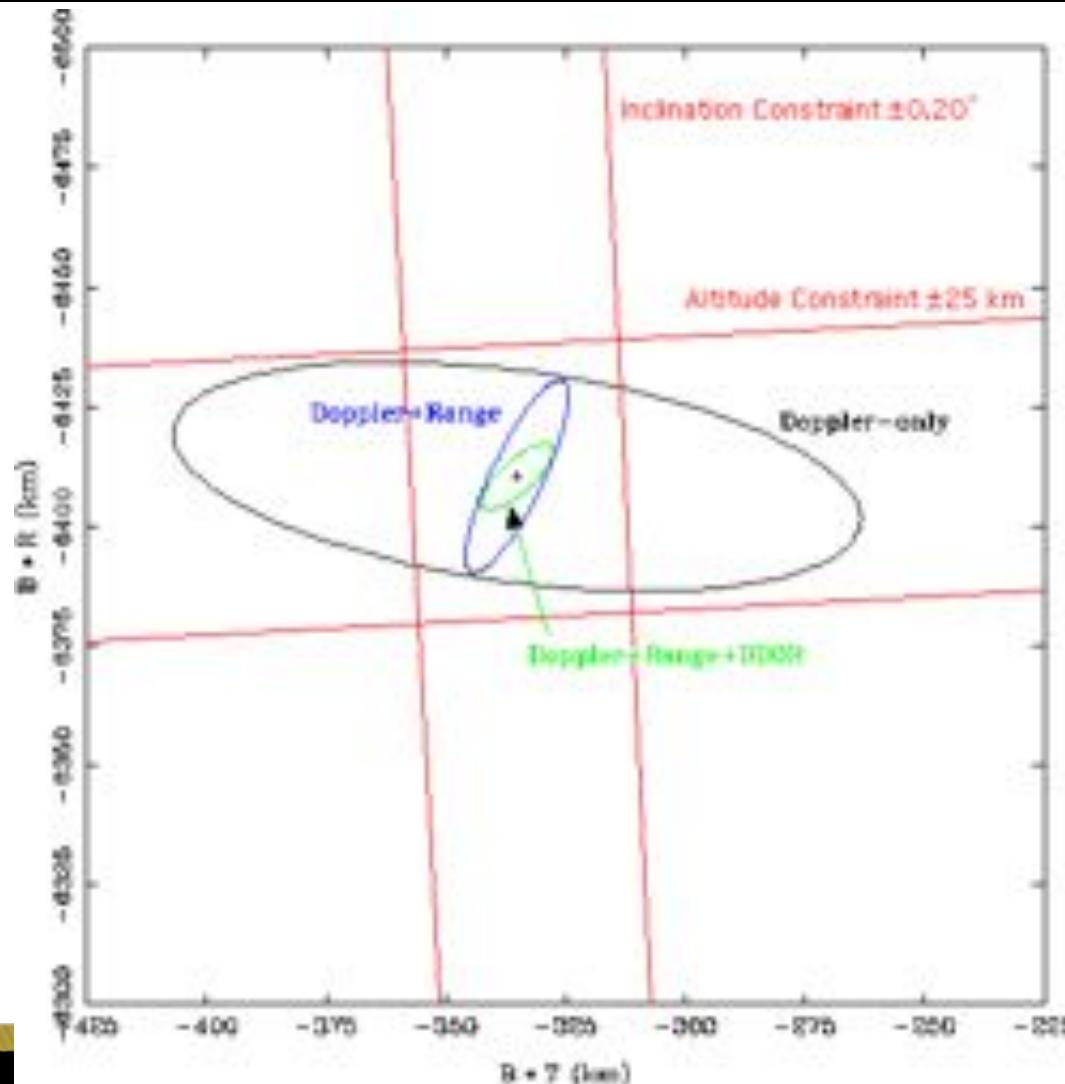
### TCM-4 to Correct Miss

$\Delta V$ : 0.08 m/s



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# Data Type Contributions to Solution



OD Knowledge  
at the time of  
TCM-4 Design ( $3\sigma$ )

Goal:  
Altitude:  $300 \text{ km} \pm 25 \text{ km}$   
Inclination:  $93.5^\circ \pm 0.2^\circ$

Achieved:  
Altitude:  $300.75 \text{ km}$   
Inclination:  $93.51^\circ$



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# Other interplanetary missions

- ▶ If ODY required 4 TCMs to achieve a good insertion, imagine what Cassini goes through.
- ▶ Cassini:
  - 2 Venus flybys
  - 1 Earth flyby
  - 1 Jupiter flyby
  - 90+ Titan flybys
  - Dozens of other targeted satellite flybys
  - Total number of OD solutions? Thousands.



# Lessons Learned from CH-1

- ▶ Fast and furious can achieve success.
  - Often eats into fuel budget
  - Have to be prepared to work rapidly
- ▶ Good practice to:
  - Think through all possible outcomes.
  - Include time for contingencies.
  - Have a contingency plan at all times.



# GRAIL's Navigation Plan

- ▶ GRAIL's operations have been planned to avoid conflicts between the two spacecraft.
  - Only one spacecraft is performing a maneuver on a given day.
  - A 5-day maneuver design block precedes any significant maneuver design. Contingencies can reduce this to a 3-day, 5-shift block.
    - This is at least 5 times more time than we had for CH-1!
  - Many contingency plans exist.



# Earth Orbiters

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- ▶ Huge difference between interplanetary and Earth orbiters
  - Short data arcs
  - Good geometry variations
  - Many potential tracking stations
  - Other data types
    - Radiometric, GPS, optical, GBORN
  - No significant light-time operational issues
  - Often tighter absolute requirements
  - Collision avoidance
  - So many Earth orbiters!



# Techniques for OD Solution Accuracy Assessment

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Examine  $P$ , the estimation error variance-covariance matrix

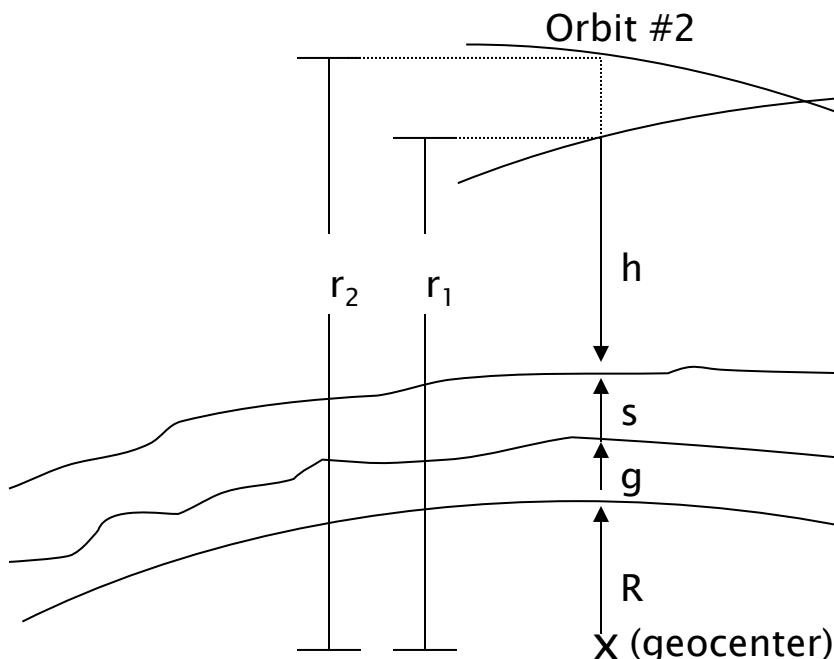
1. Plot tracking data residuals
  - Are they Gaussian?
  - What is the mean and RMS for each data type?
  - If these agree with the *a priori* data statistics, one can believe that  $P$  actually represents the estimation errors – this will probably never happen.
2. In general the correlations in  $P$  will be nearly correct but the variances will be optimistic unless process noise has been added and properly calibrated (tuned).
3. Do solution overlaps and compute statistics on them
  - Any common biases will cancel



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# Techniques for OD Solution Accuracy Assessment

4. If the spacecraft has laser tracking compare spacecraft slant range computed from OD solutions with withheld laser range measurements. Lasers are generally accurate to 1 or 2 cm.
5. If the spacecraft carries an altimeter, examine cross over differences over the ocean or any point where the altimeter measures accurately and local surface elevation is constant.



$r_1, r_2$  = OD solutions,  
radius from geocenter  
 $e_1, e_2$  = orbit error  
 $h$  = altimeter measurement  
 $r_1 - h_1 = R + g + s + e_1 = C_1$   
 $r_2 - h_2 = R + g + s + e_2 = C_2$   
 $C_1 - C_2$  = orbit error less  
common biases  
surface  
geoid  
ellipsoid

# The End

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## ► Statistical Orbit Determination

- The art of gracefully knowing that you don't know where your satellite is.
- But now you can determine just how limited your uncertainty is!
- Stat OD II will delve into more operational details, such as consider filters, unscented Kalman filters, more process noise, smoothing, and other topics to help you keep your \$1B satellite flying straight.



# The End

- ▶ Check your grades (for those graded anyway), especially quizzes.
- ▶ Exam 3 out today – due Monday at midnight unless you get permission otherwise.
- ▶ Thursday work day in this room.
- ▶ Everything else due Dec 20. Let me know if this is a problem!

December 2012						
Sun	Mon	Tue	Wed	Thu	Fri	Sat
						1
2	3	4	5	6	7	8
9	10	11	12	13	14	15
16	17	18	19	20	21	22
23	24	25	26	27	28	29
30	31					

Take-Home  
Exam Due



Final Project  
Due  
All HW Due



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