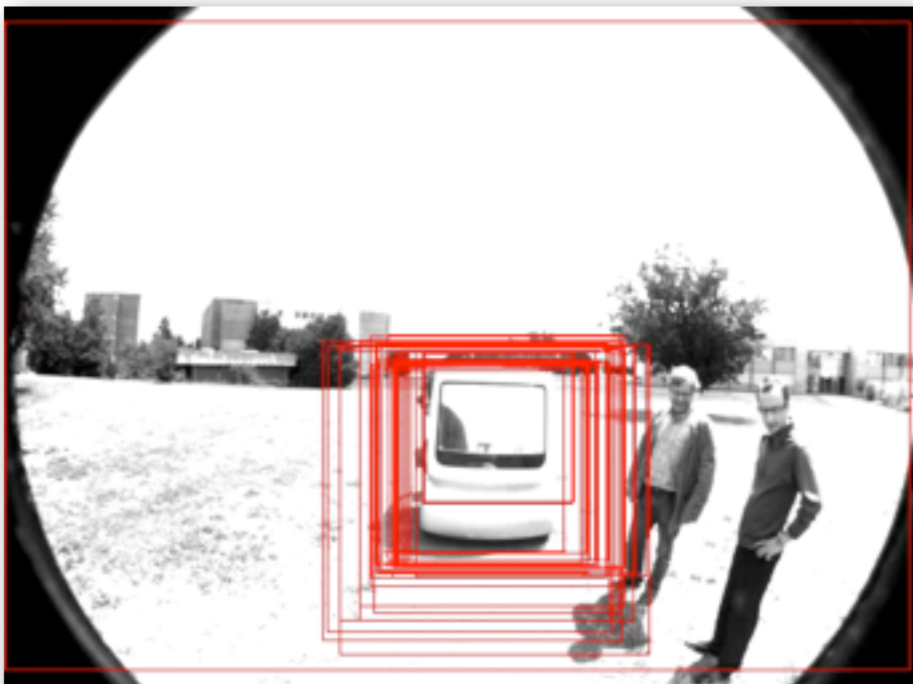
Particle Filters for Visual Tracking

T. Chateau, Pascal Institute, Clermont-Ferrand



Content

- Particle filtering: a probabilistic framework
- SIR particle filter
- MCMC particle filter
- RJMCMC particle filter

Content

- **Particle filtering: a probabilistic framework**
- SIR particle filter
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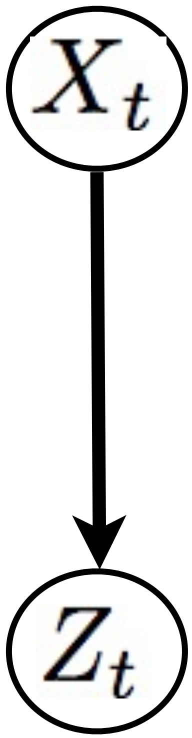
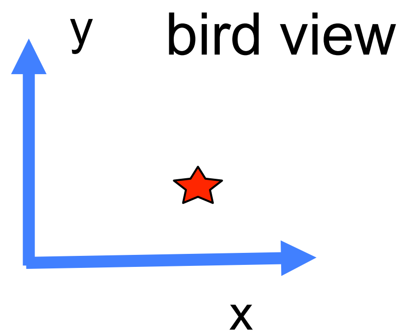
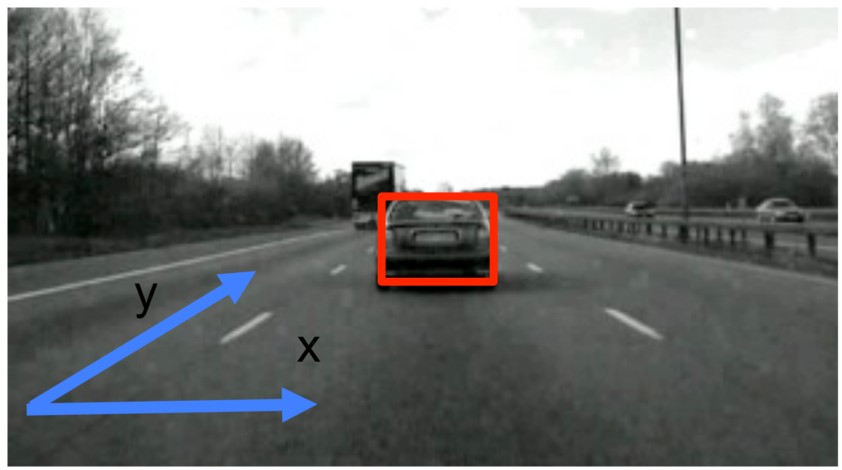
Visual Tracking

State (hidden variable)



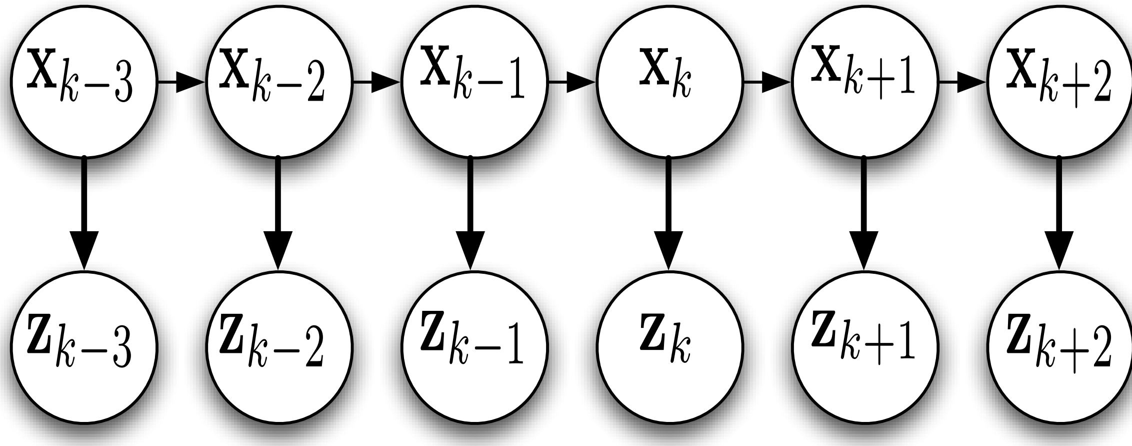
Observation





Definitions

Dynamic Bayesian Network representation



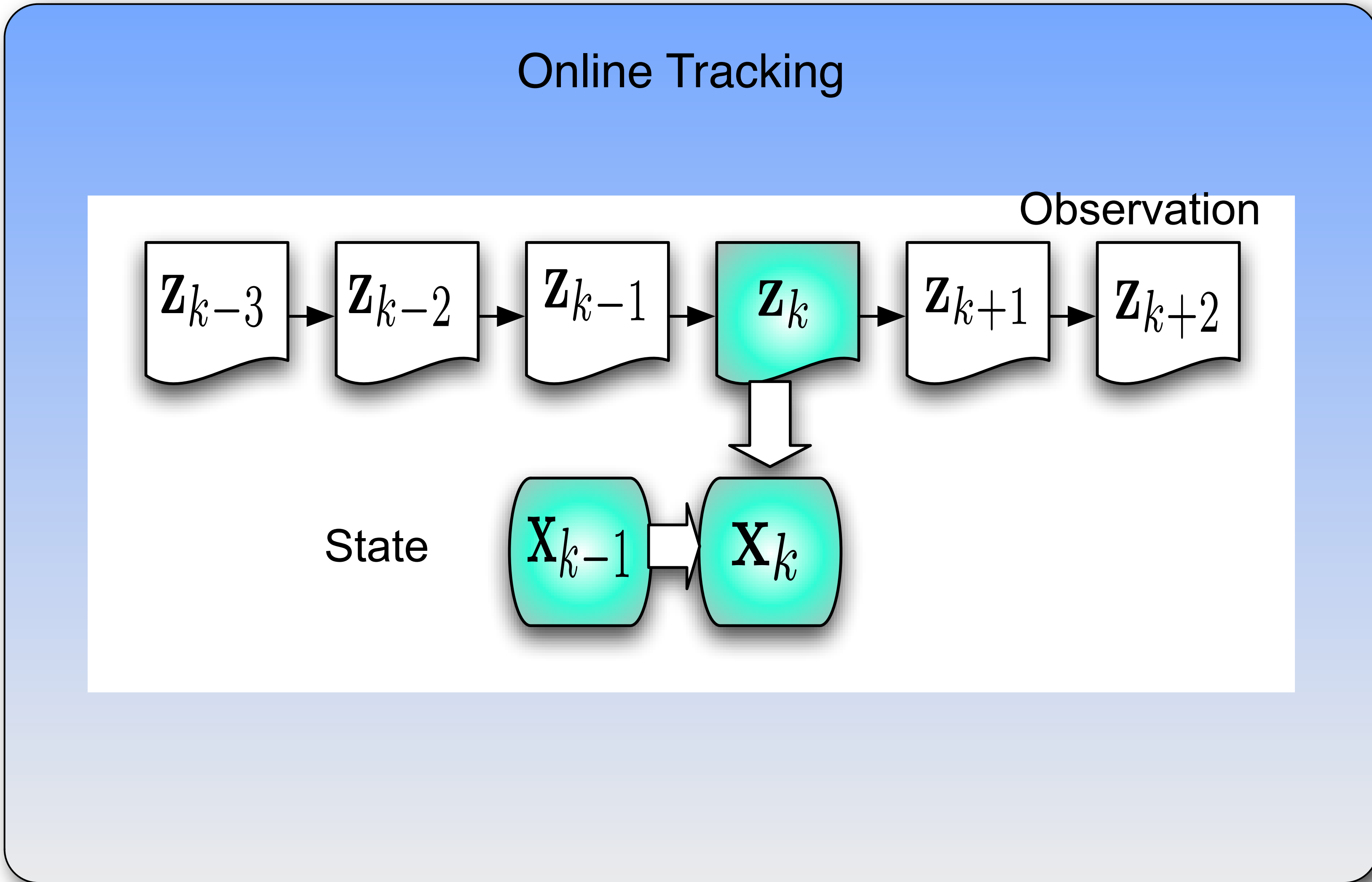
States

$$\mathbf{X} \doteq \{\mathbf{x}_k\}_{k=1,\ldots,K}$$

Observations

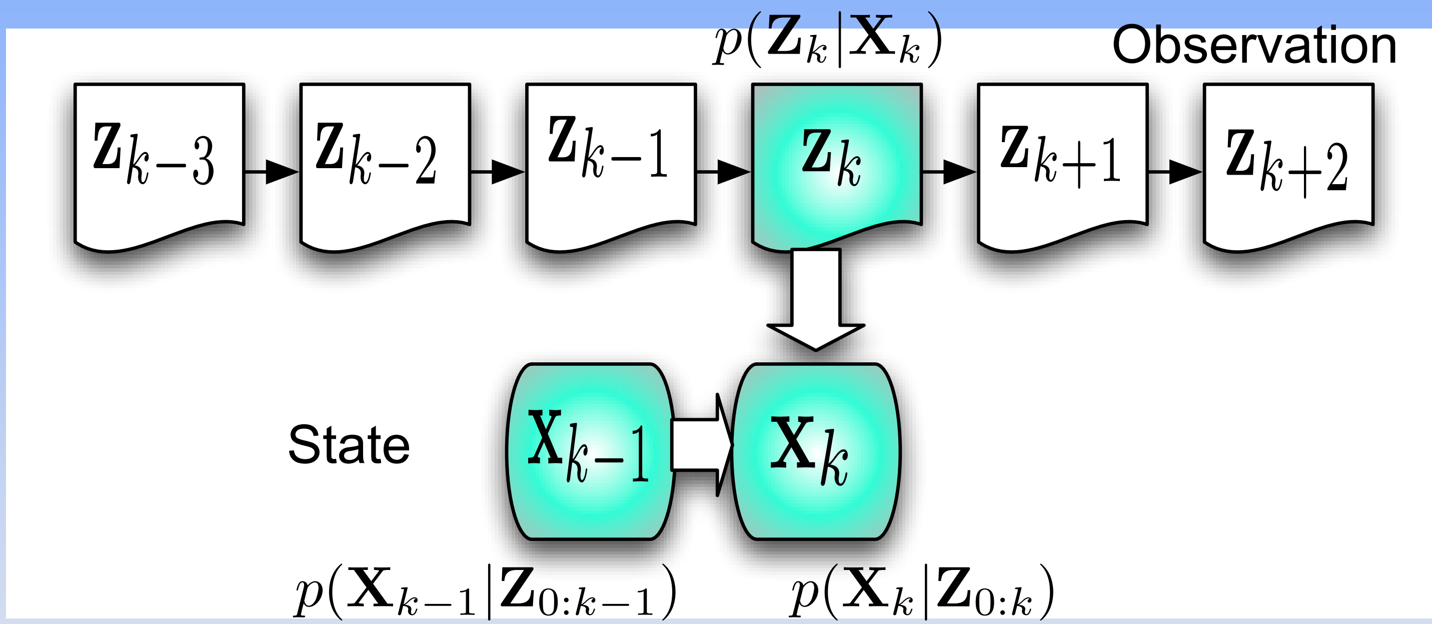
$$\mathbf{Z} \doteq \{\mathbf{z}_k\}_{k=1,\ldots,K}$$

Online Tracking

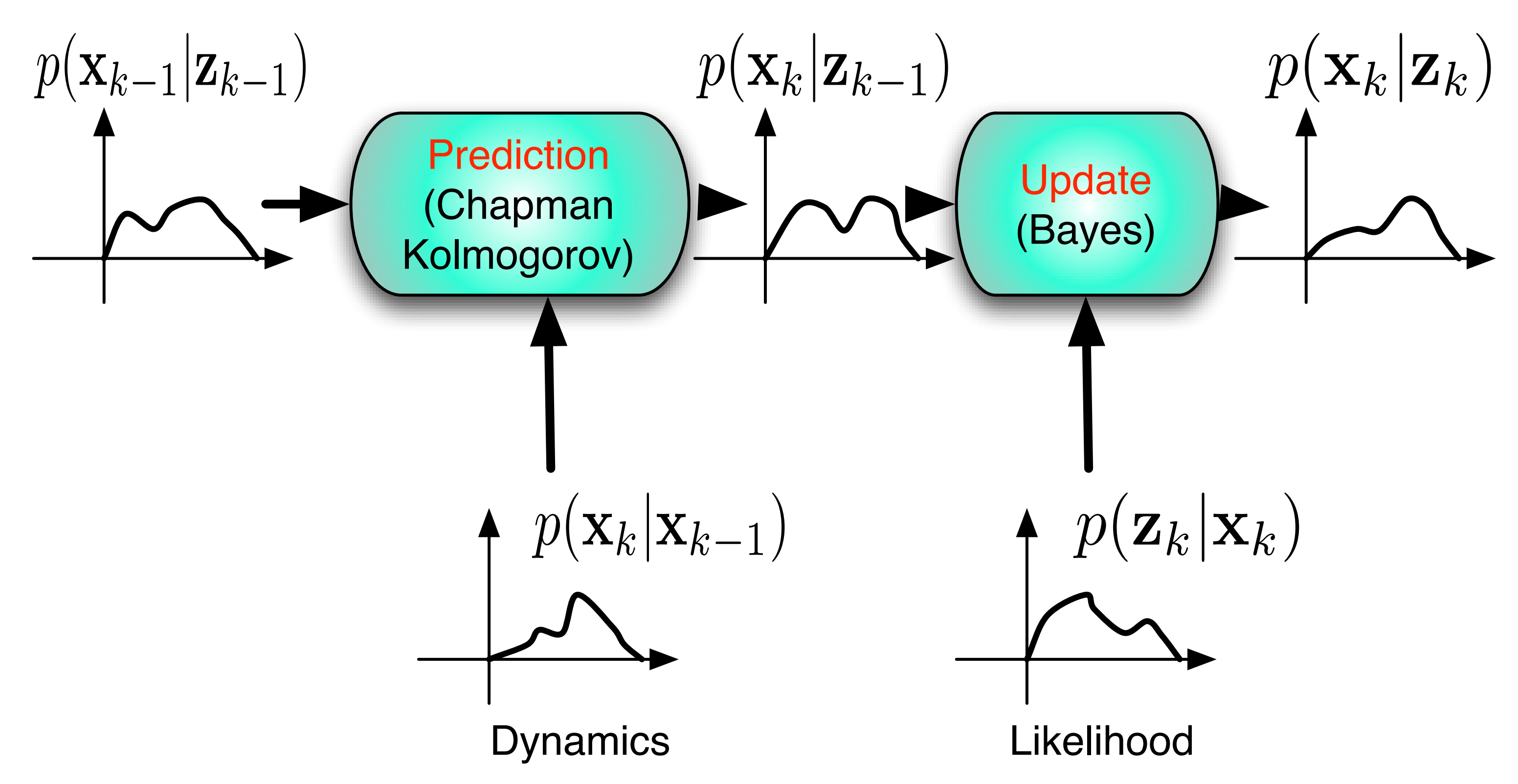


Online Tracking

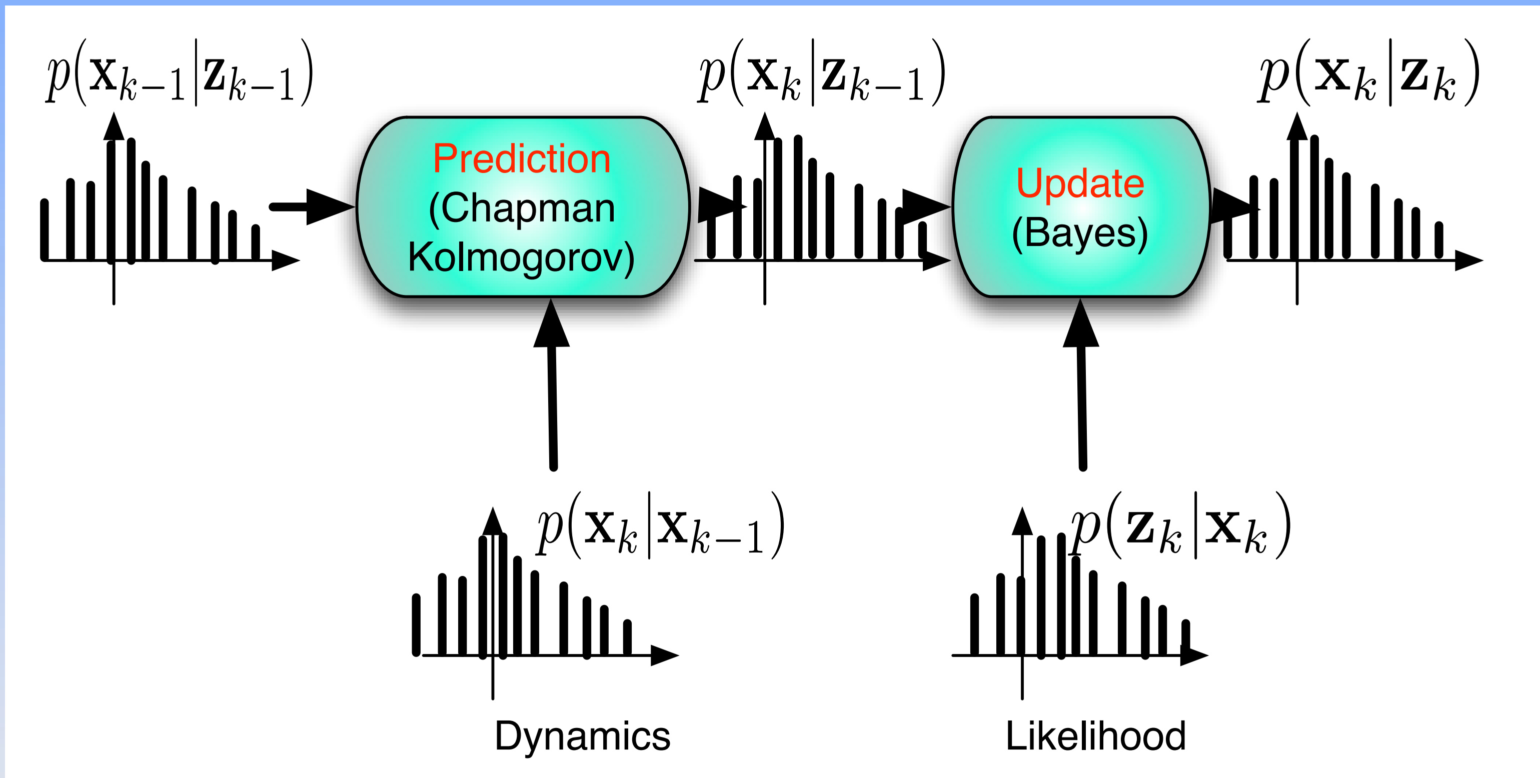
Probabilistic framework



Sequential Monte-Carlo Inference



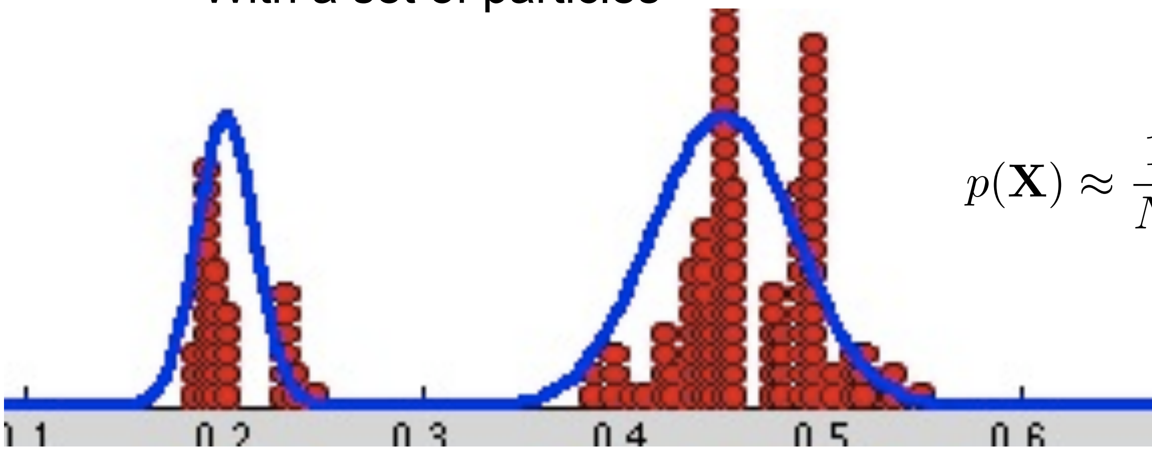
Sequential Monte-Carlo Inference



Stochastic representation of distributions

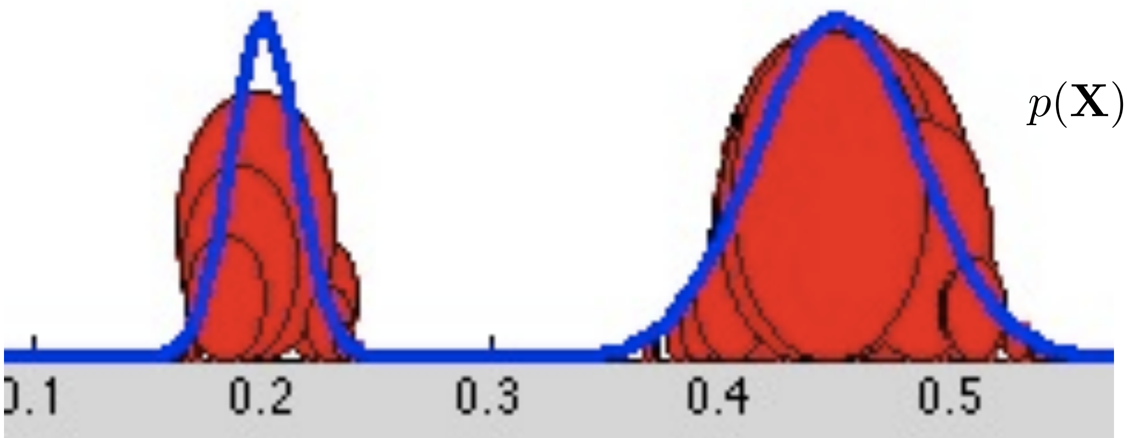
Stochastic representation of distributions

With a set of particles



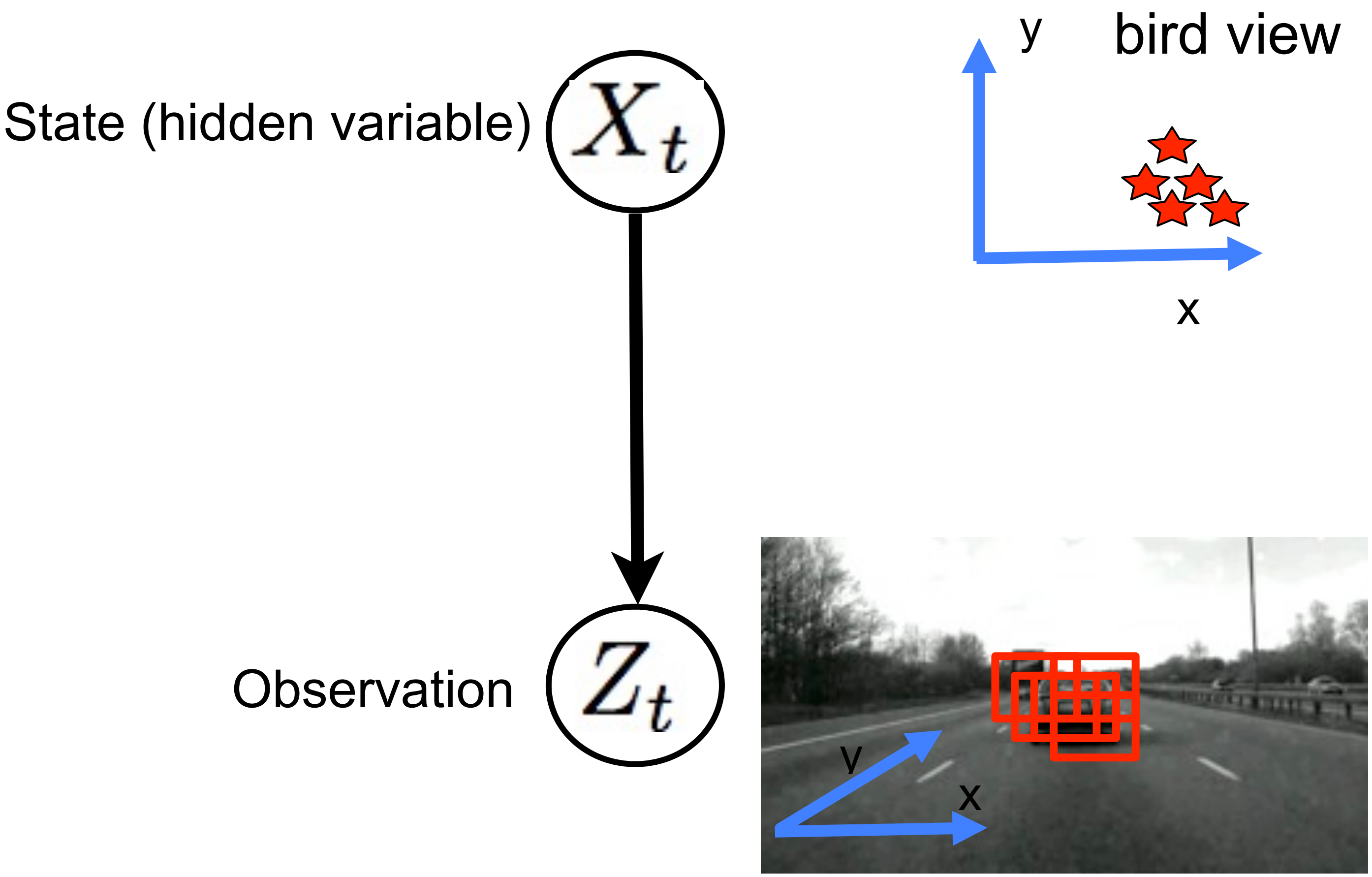
$$p(\mathbf{X}) \approx \frac{1}{N}\sum_{n=1}^{N}\delta(\mathbf{X}-\mathbf{X}^n)$$

With a set of weighted particles



$$p(\mathbf{X}) \approx \sum_{n=1}^{N}\pi^n\delta(\mathbf{X}-\mathbf{X}^n)$$

Visual Tracking



Content

- Particle filtering: a probabilistic framework
- **SIR particle filter**
- MCMC particle filter
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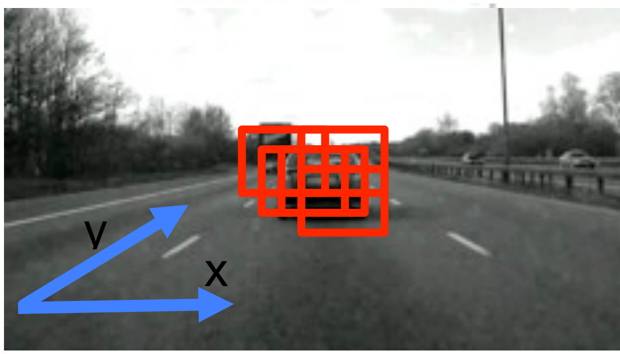
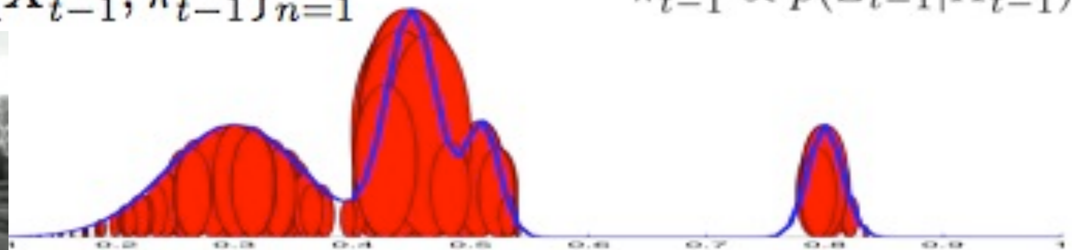
SIR Particle Filter

Sampling Importance Resampling

$$p(X_{t-1}|Z_{0:t-1}) \approx \{X_{t-1}^n, \pi_{t-1}^n\}_{n=1}^N \qquad \pi_{t-1}^n \propto p(Z_{t-1}|X_{t-1}^n)$$

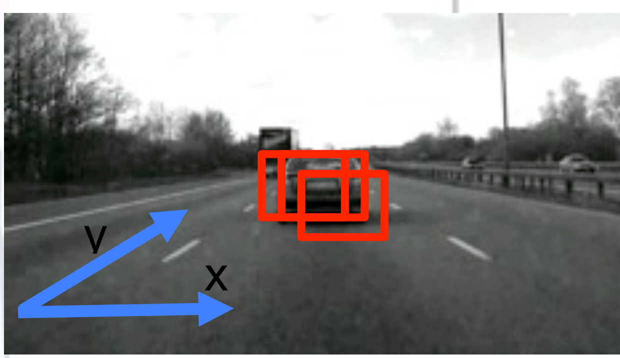


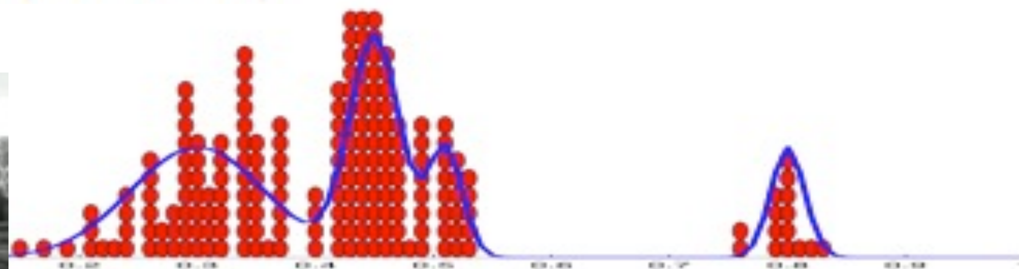


State distribution at time *t-1*

Resampling

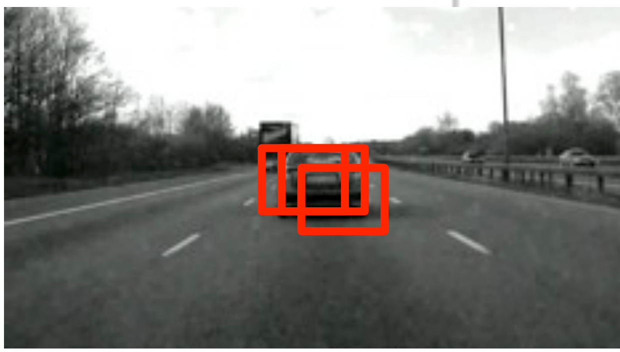
$$p(X_{t-1}|Z_{0:t-1}) \approx \{X_{t-1}^{n*}, 1/N\}_{n=1}^N$$

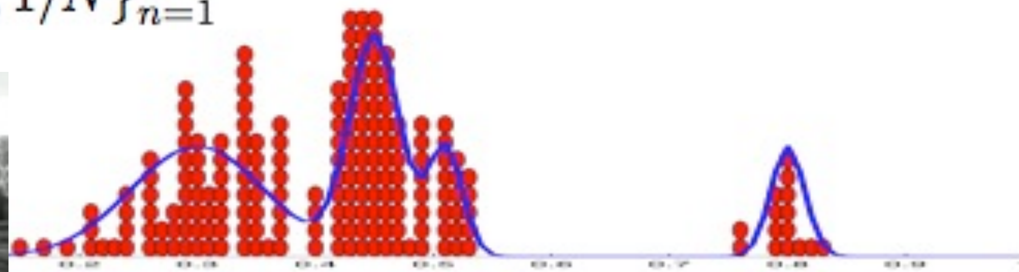




SIR Particle Filter

$$p(X_{t-1}|Z_{0:t-1}) \approx \{X_{t-1}^{n*}, 1/N\}_{n=1}^{N}$$



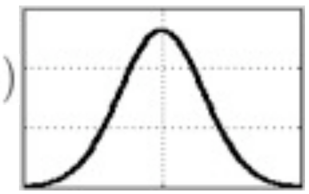


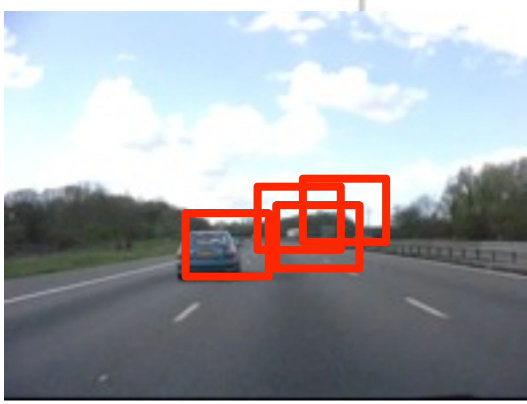
State distribution at time *t-1*

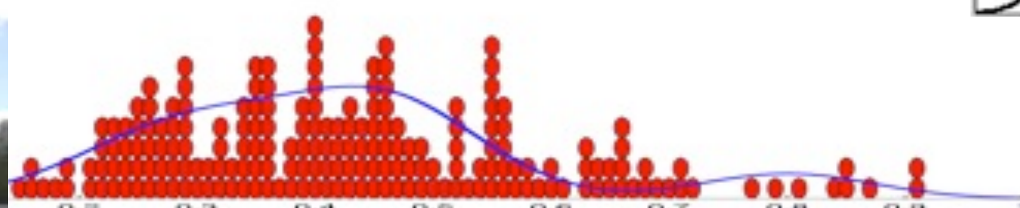
Prediction

$$p(X_t|X_{t-1}, Z_{0:t-1}) \approx \{X_t^n, 1/N\}_{n=1}^{N}$$

$q(X_t|X_{t-1})$



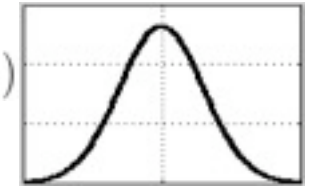


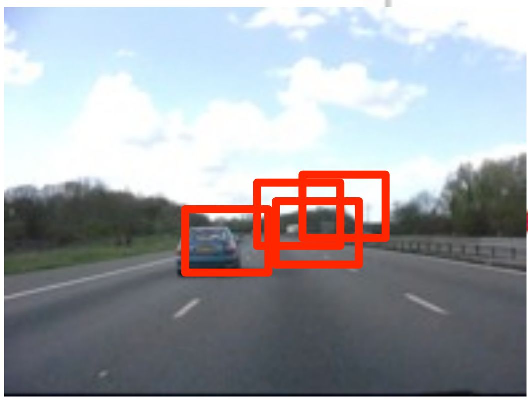


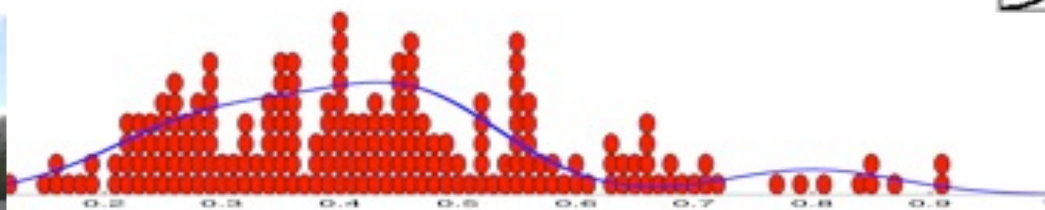
SIR Particle Filter

$$p(X_t|X_{t-1}, Z_{0:t-1}) \approx \{X_t^n, 1/N\}_{n=1}^N$$

$q(X_t|X_{t-1})$





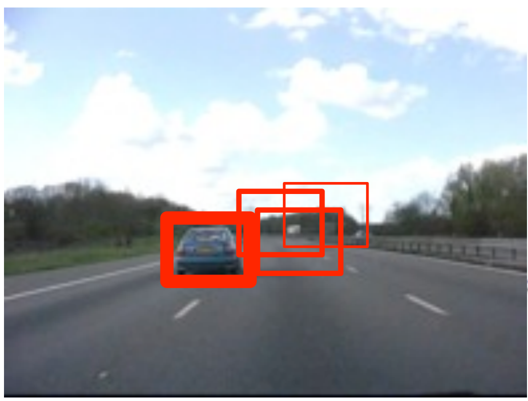


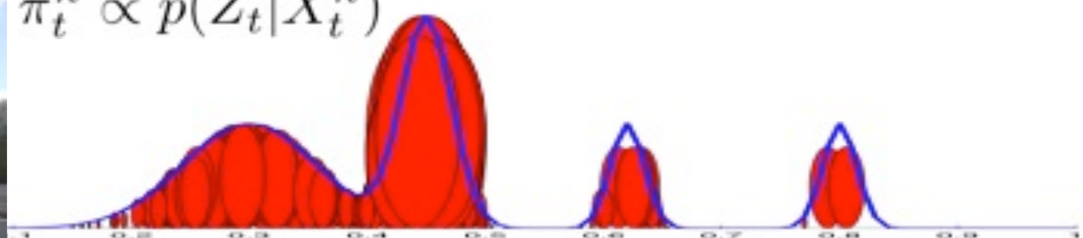
Predicted distribution at time *t*

Update

$$p(X_t|Z_{0:t}) \approx \{X_t^n, \pi_t^n\}_{n=1}^N$$

$\pi_t^n \propto p(Z_t|X_t^n)$

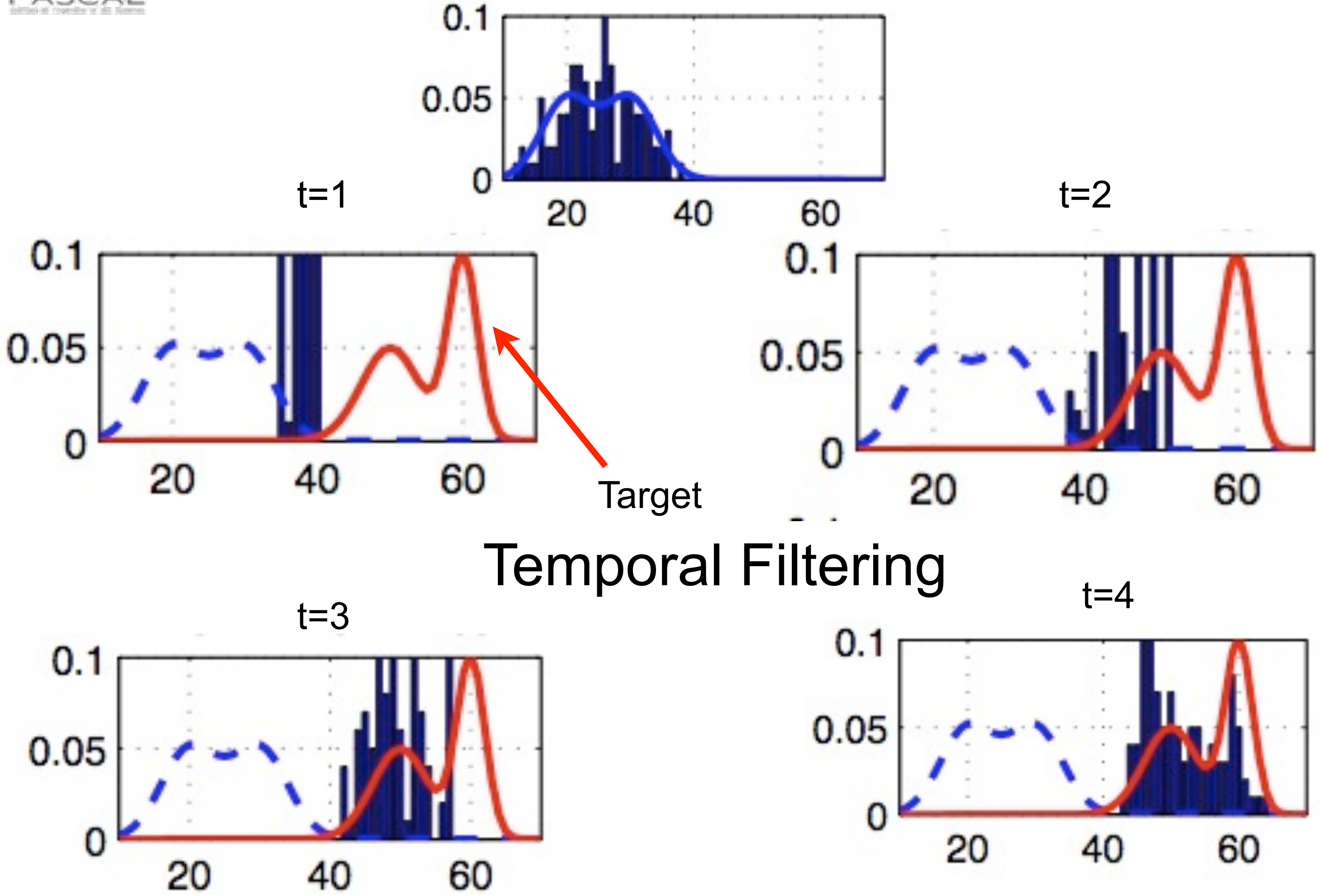




Posterior

S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp. A tutorial on particle filters for on-line non-linear/non-gaussian bayesian tracking. *IEEE Transactions on Signal Processing*, 50(2):174–188, Feb. 2002.

SIR Particle Filter

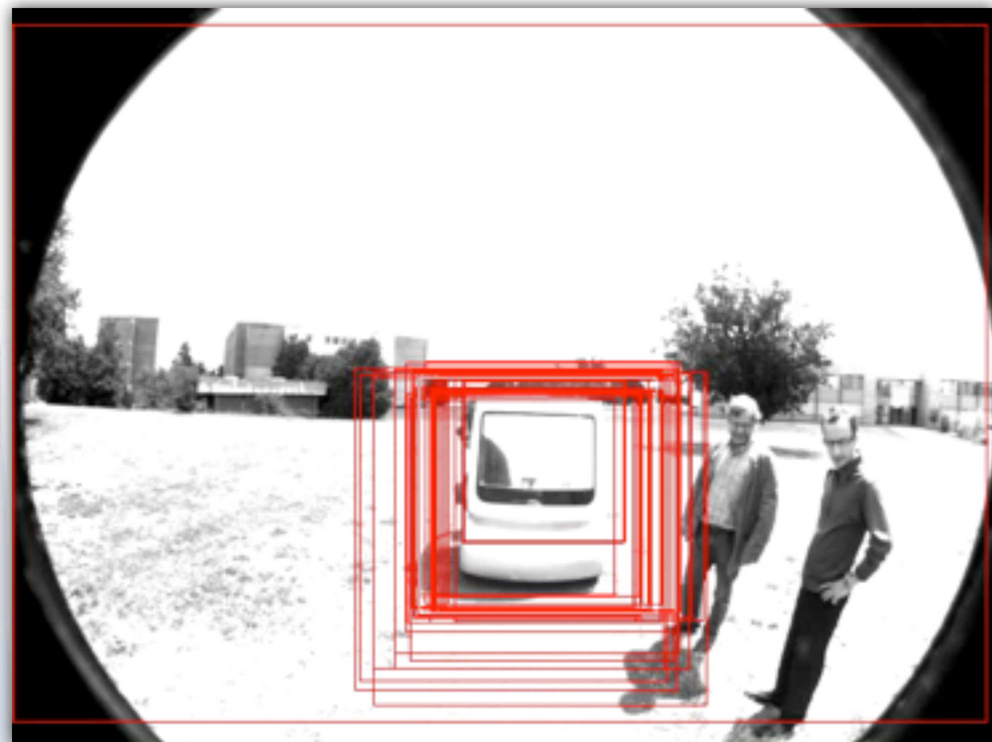


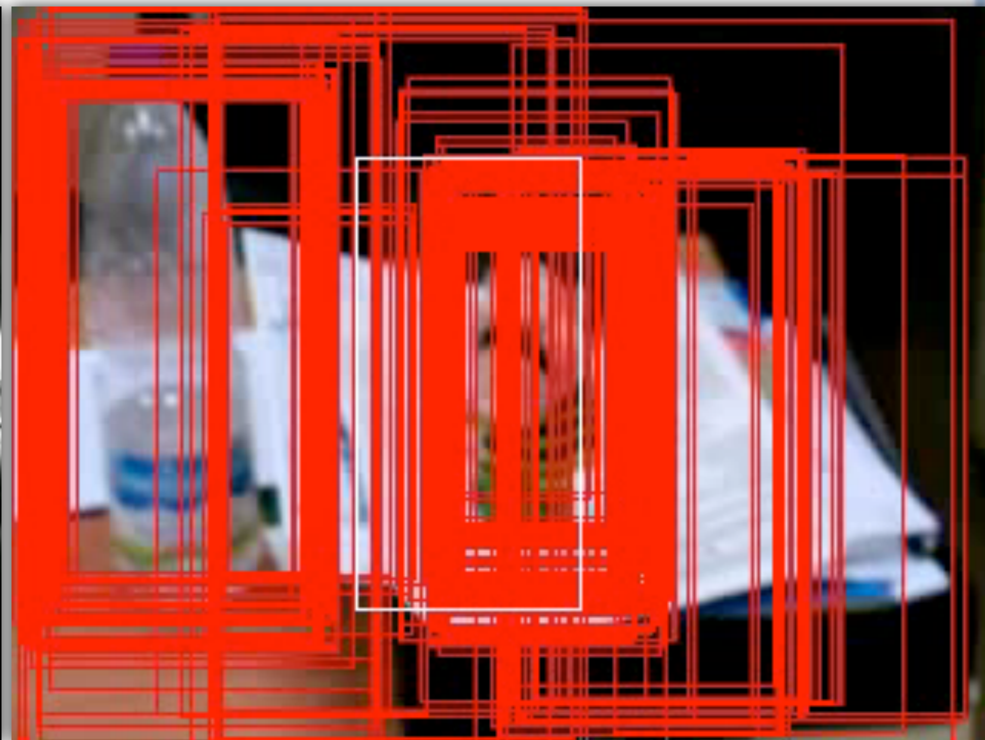
SIR Particle Filter: some examples

- State vector: 2D position and scale (image reference frame)
- Dynamics: random step
- Observation model: max. of gradients set of points

T. Chateau and J. Laprest√©. Robust real time tracking of a vehicle by image processing. In *IEEE Intelligent Vehicles Symposium,*, Parma, Italy, June 2004.

SIR Particle Filter: some examples

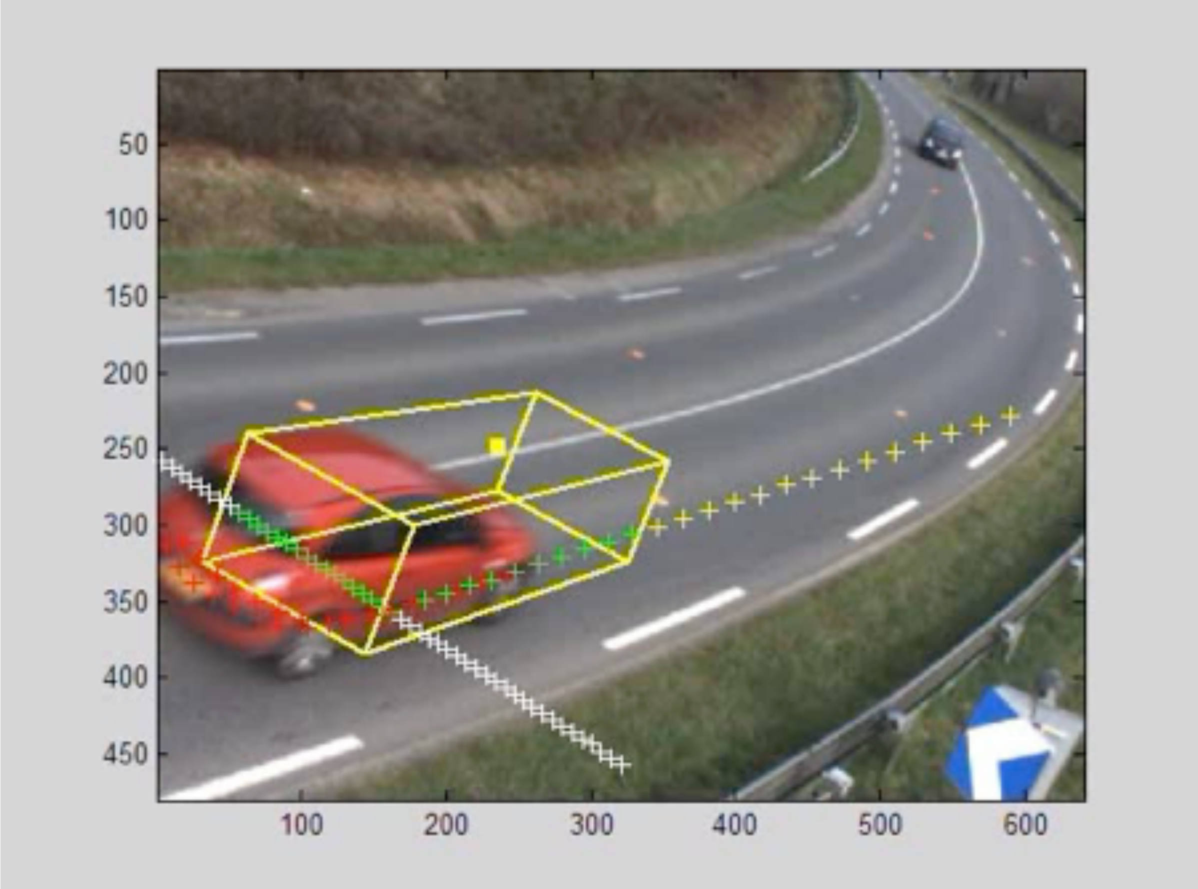




- State vector: 2D position and scale (image reference frame)
- Dynamics: random step
- Observation model: offline learning based model (Haar wavelets)

T. Chateau, V. Gay-Belille, F. Chausse, and J. T. Lapresté. Real-time tracking with classifiers. In *WDV - WDV Workshop on Dynamical Vision at ECCV2006*, Grazz, Austria, May 2006.

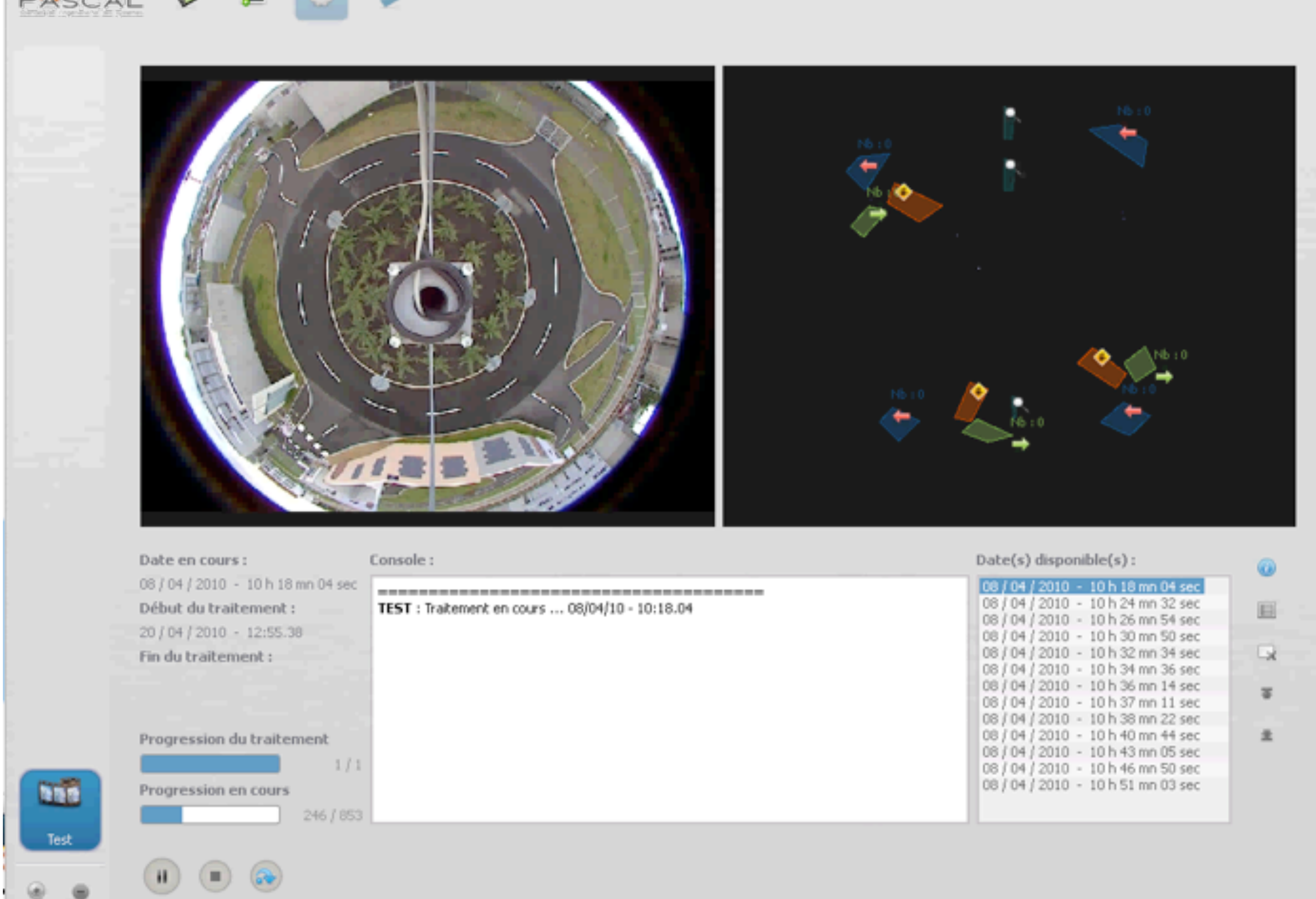
SIR Particle Filter: some examples



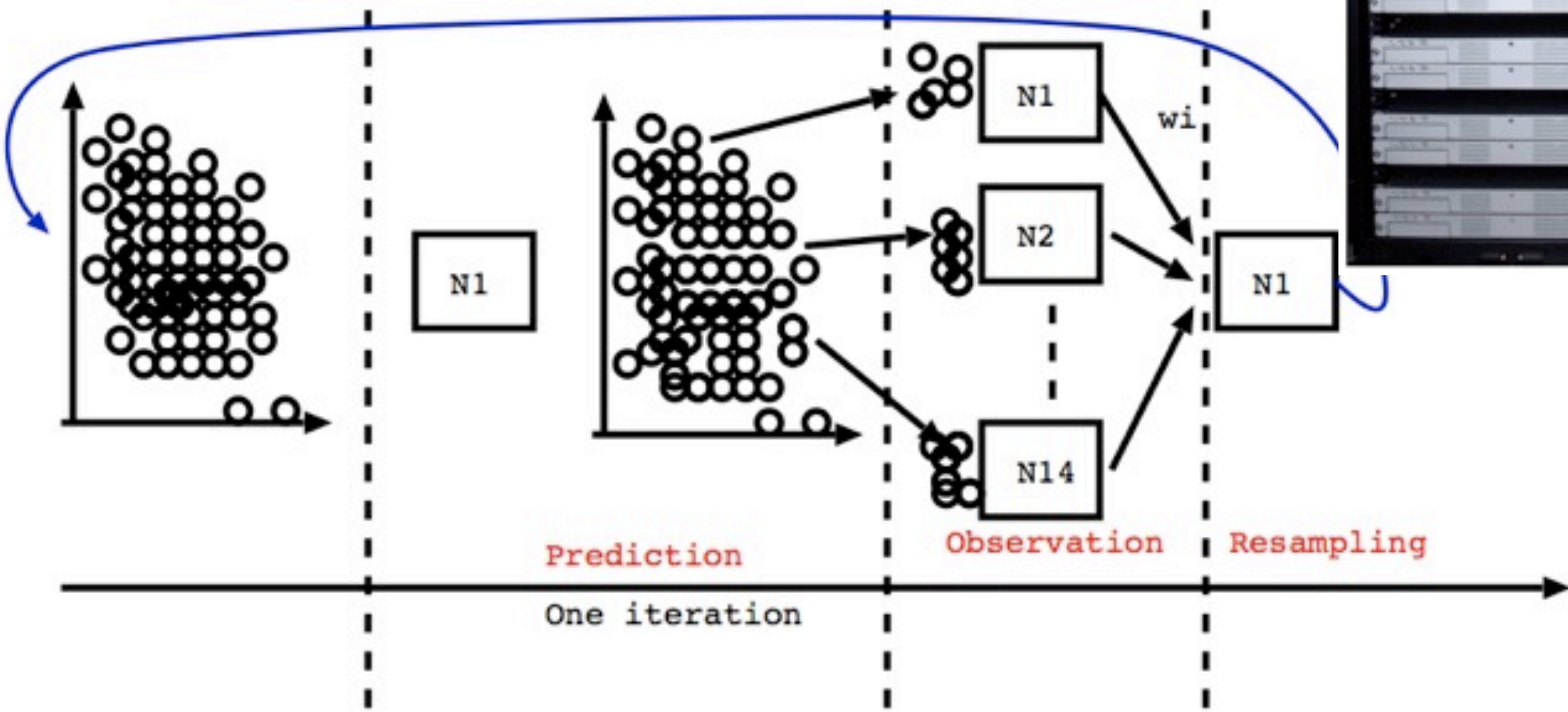
- State vector: 3D position, orientation, steering angle and velocity
- Dynamics: driven by a bicycle model
- Observation model: background/foreground subtraction, camera and laser range finder
- Collaboration with LCPC Nantes

Y. Goyat, T. Chateau, and L. Trassoudaine. Tracking of vehicle trajectory by combining a camera and a laser rangefinder. *Springer MVA : Machine Vision and Application*, online, March 2009.

SIR Particle Filter: some examples



Efficient implementation of SIR Particle Filters



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Efficient implementation of Particle Filters

SIR Particle Filter

	200	500	1000	5000	10000
Seq.	0.0609s	0.1439s	0.2874s	1.6393s	3.8462s
	16.40	6.95	3.48	0.61	0.26
Par.	0.0231s	0.0265s	0.0313s	0.0858s	0.1567s
	43.31	37.72	31.9	11.66	6.38
Gain	$\times$2.7	$\times$5.42	$\times$9.16	$\times$19.43	$\times$24.5

- 20 FPS with 2000 particles .

$$N \propto e^d$$

N: number of particles
d : size of the state vector

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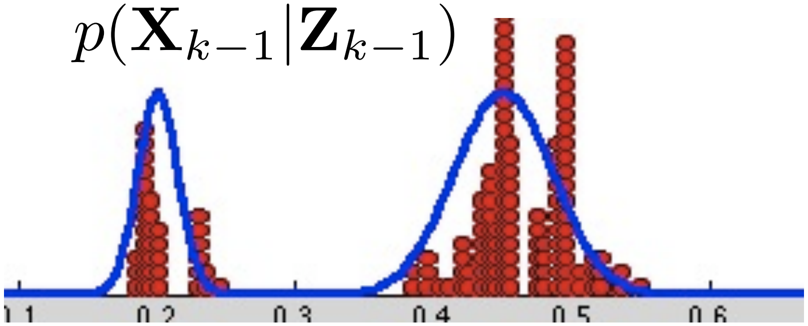
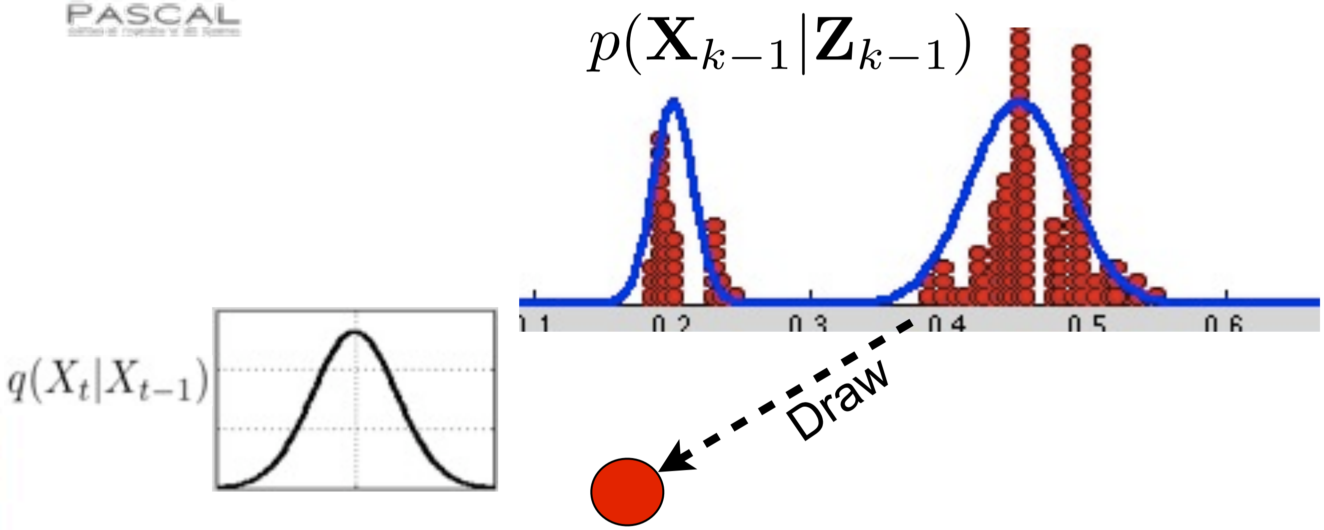
MCMC Particle Filter

$p(\mathbf{X}_{k-1}|\mathbf{Z}_{k-1})$



MCMC Particle Filter



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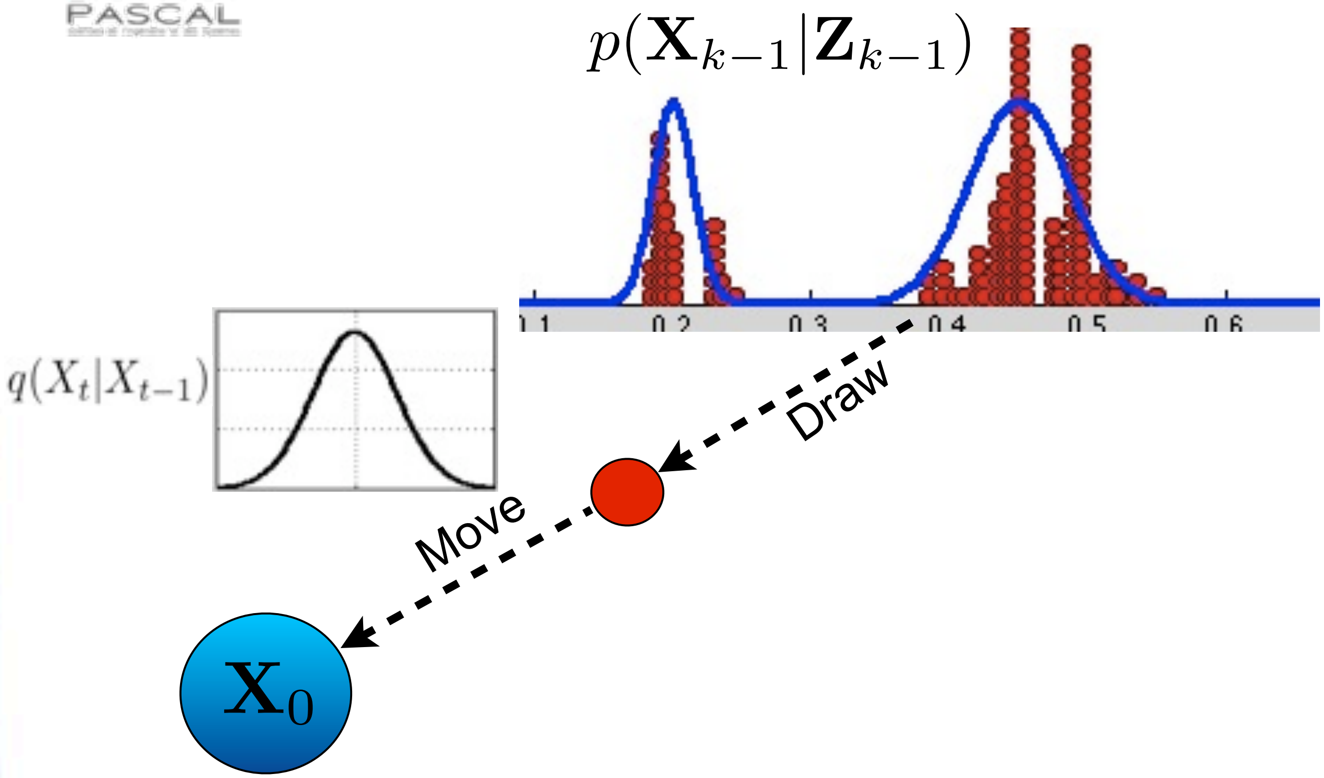
MCMC Particle Filter



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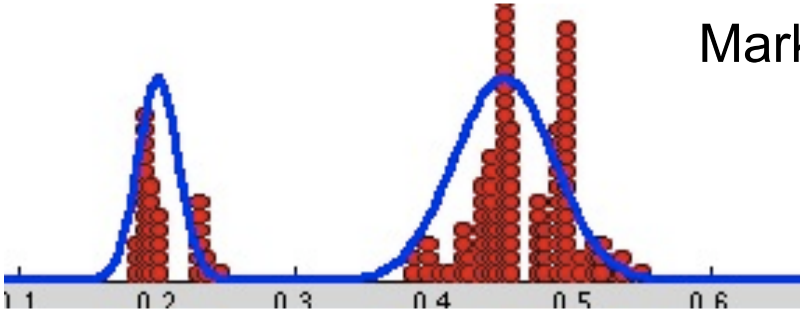
MCMC Particle Filter

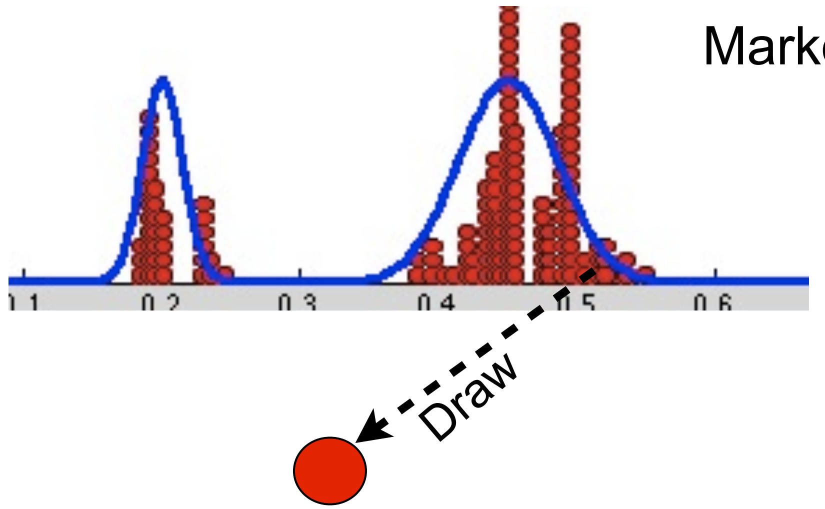


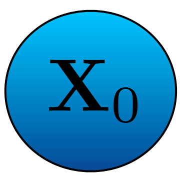
Markov Chain Monte Carlo

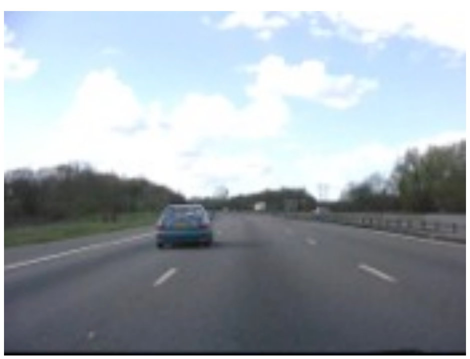
$\mathbf{X}_0$

MCMC Particle Filter

Markov Chain Monte Carlo







MCMC Particle Filter

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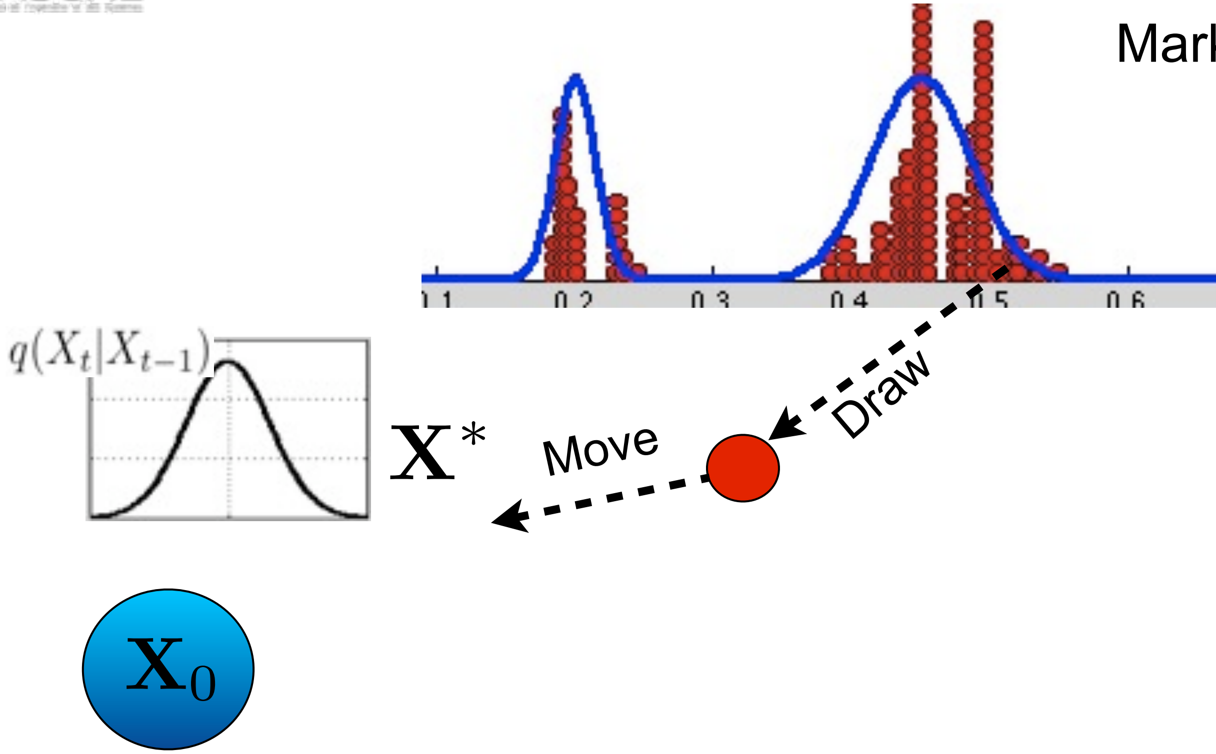

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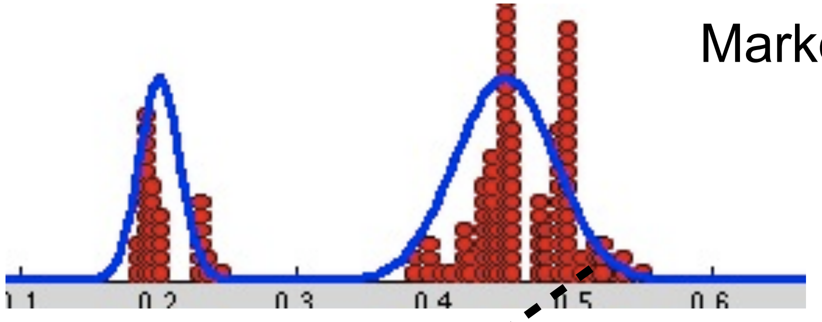

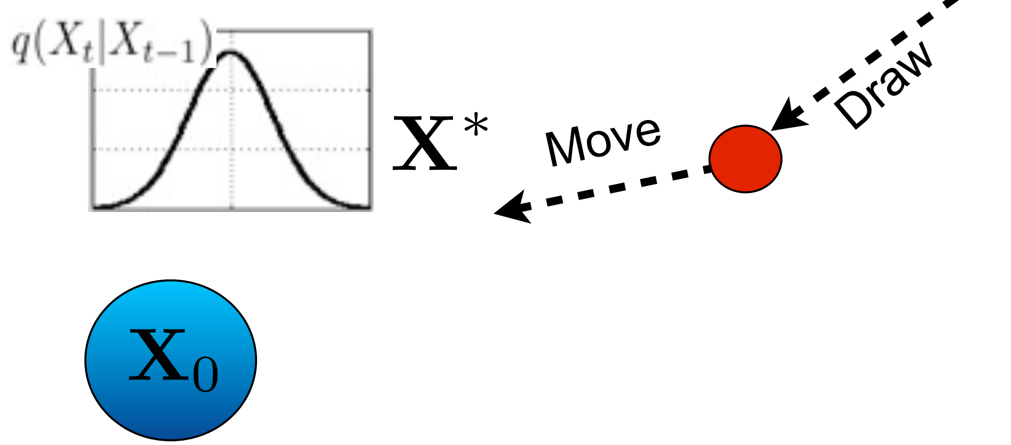

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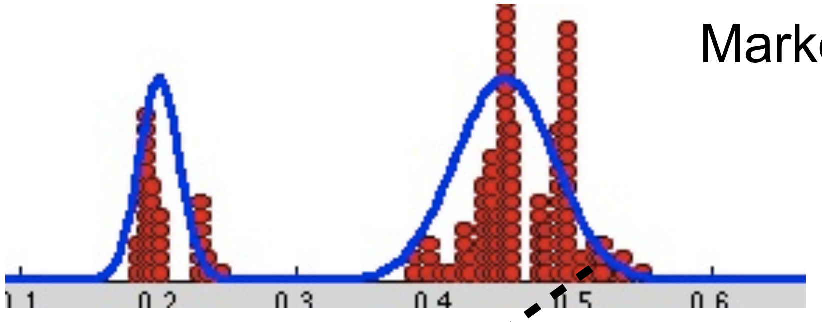
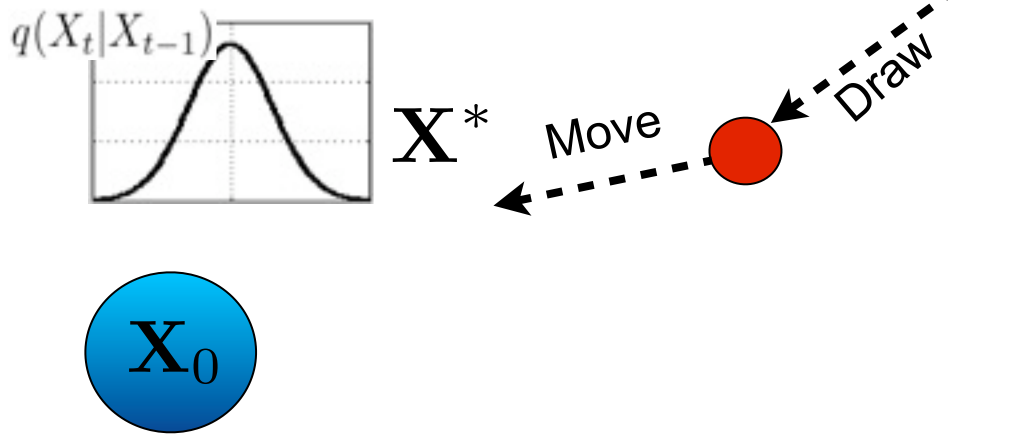
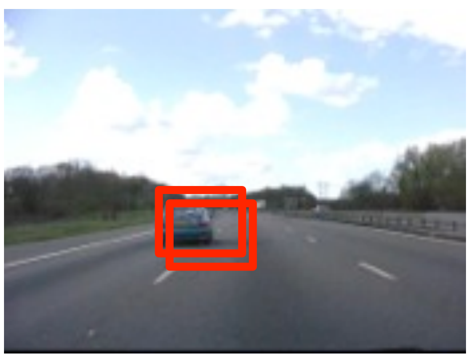
MCMC Particle Filter

Markov Chain Monte Carlo

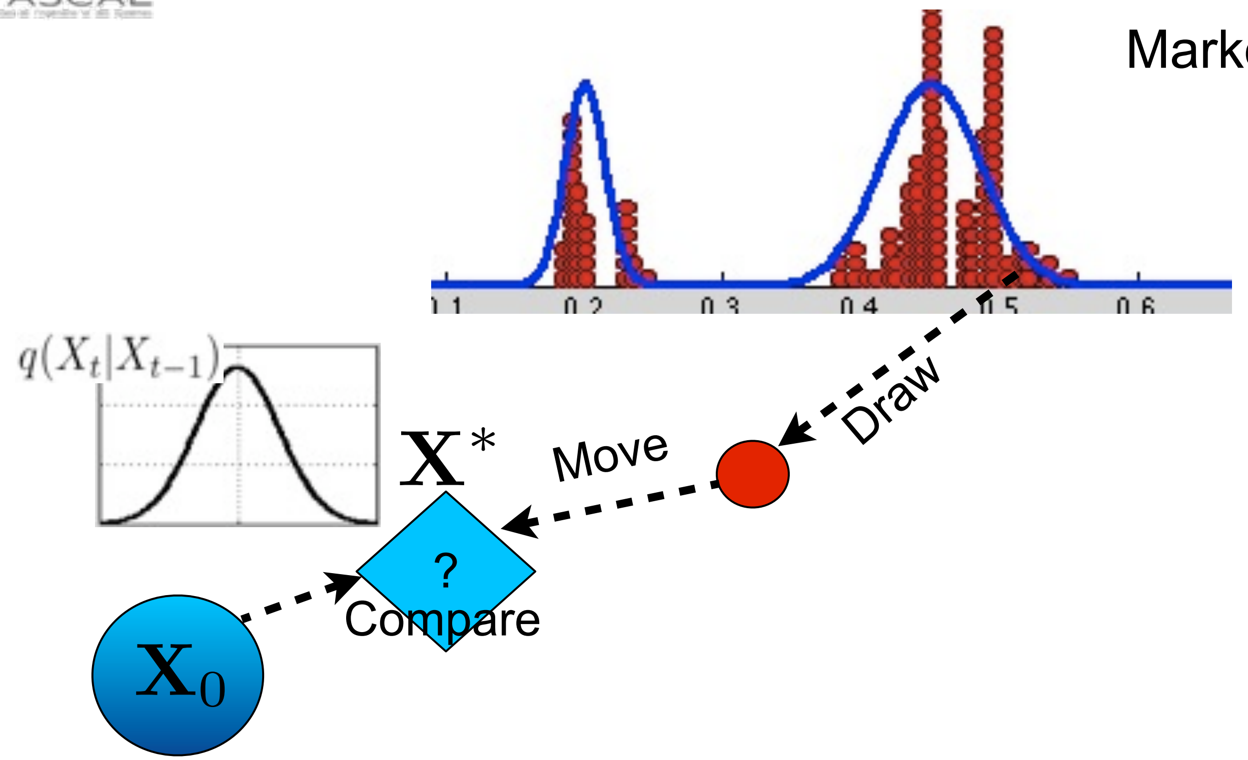


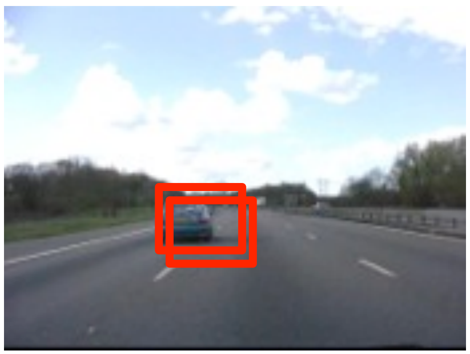




MCMC Particle Filter

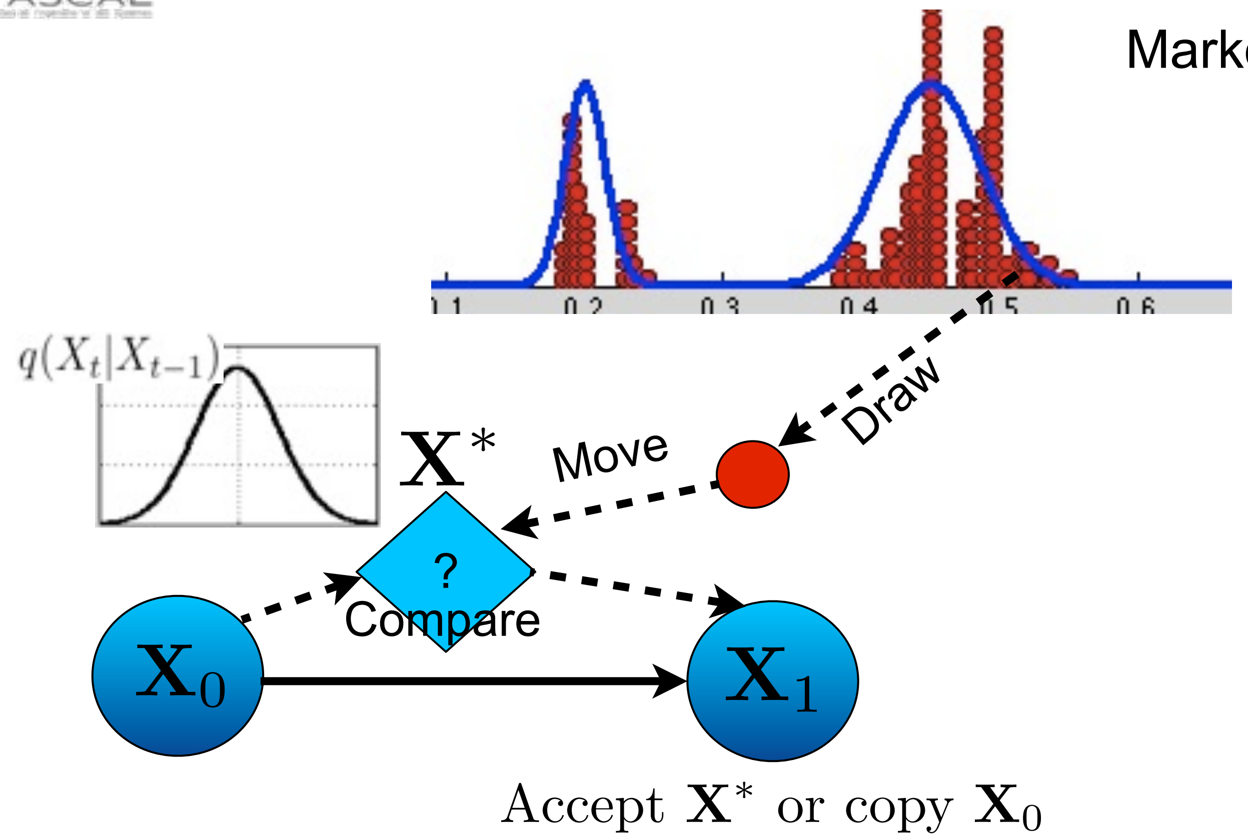
Markov Chain Monte Carlo

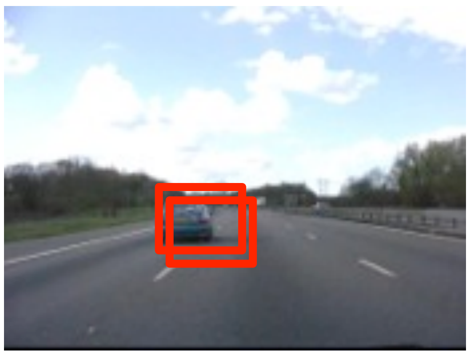




MCMC Particle Filter

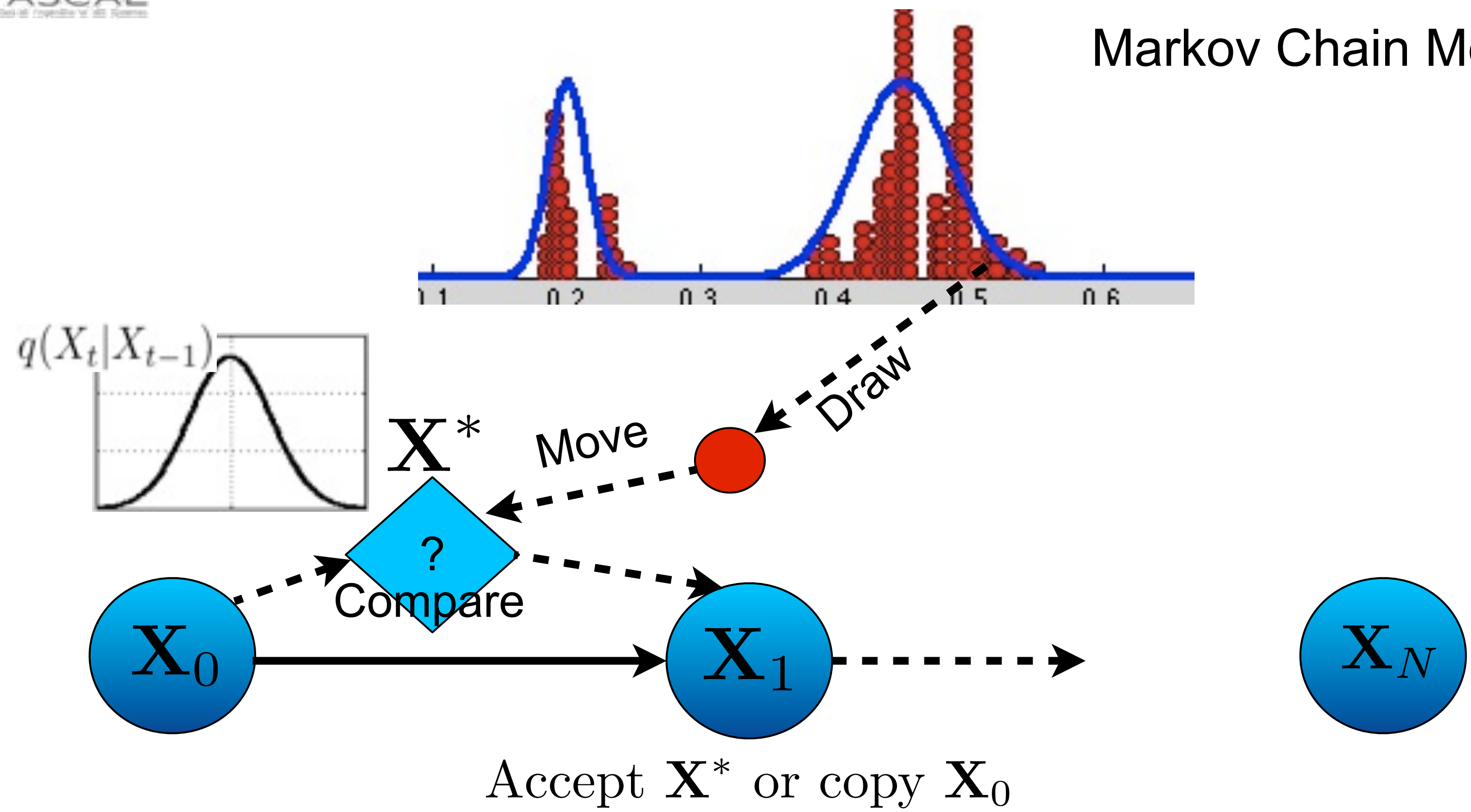
Markov Chain Monte Carlo

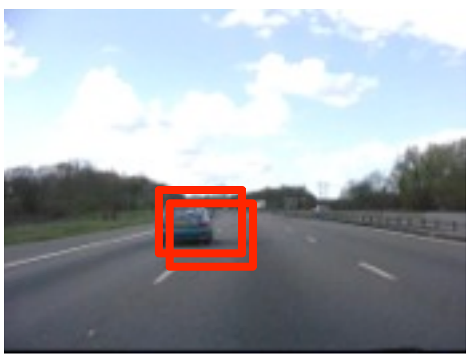




MCMC Particle Filter

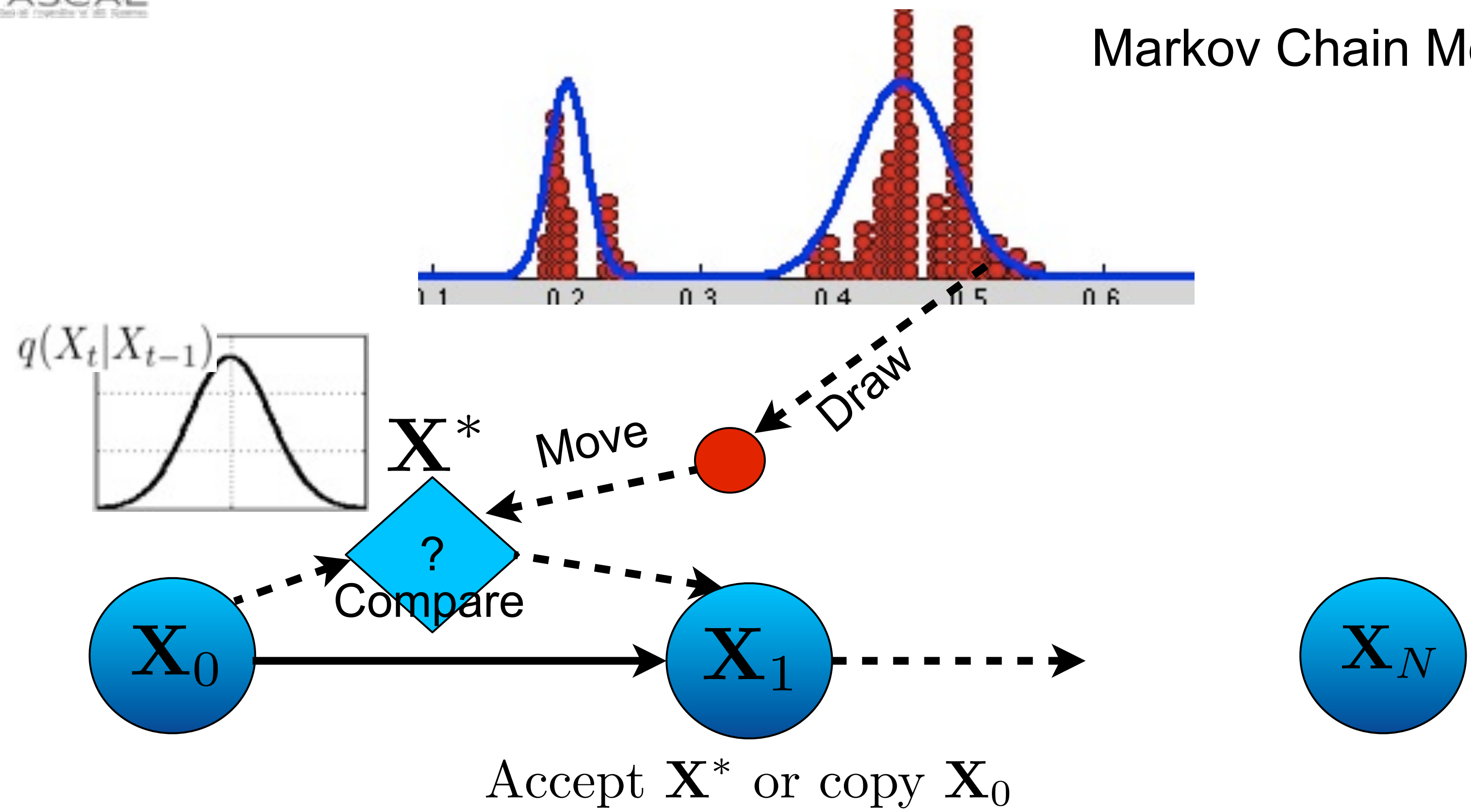
Markov Chain Monte Carlo

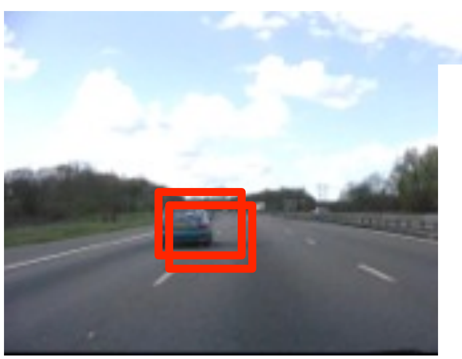


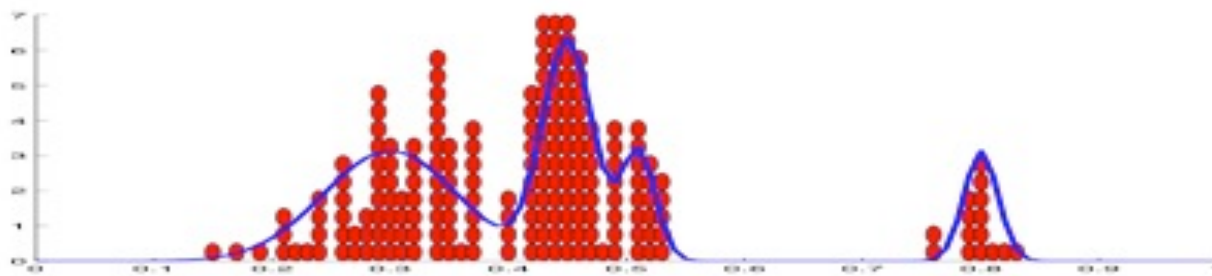


MCMC Particle Filter

Markov Chain Monte Carlo







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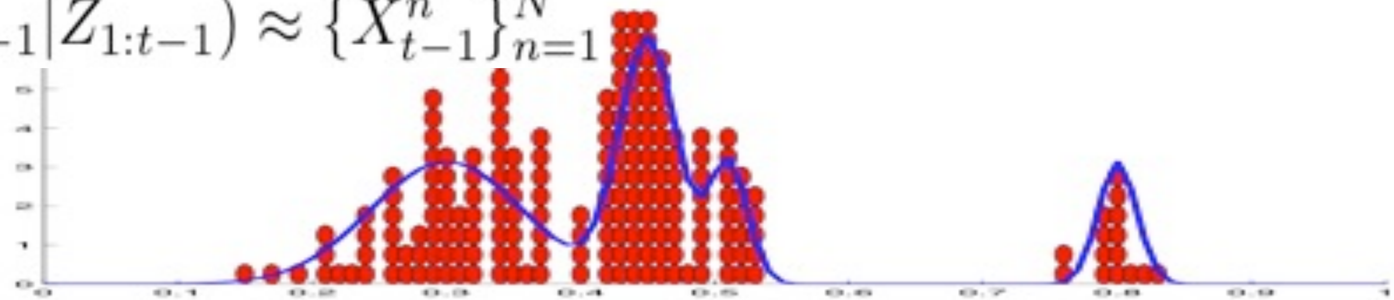
MCMC Particle Filter: marginal move

$$p(X_{t-1}|Z_{1:t-1}) \approx \{X_{t-1}^n\}_{n=1}^N$$



Metropolis Hasting rule

MCMC Particle Filter: marginal move

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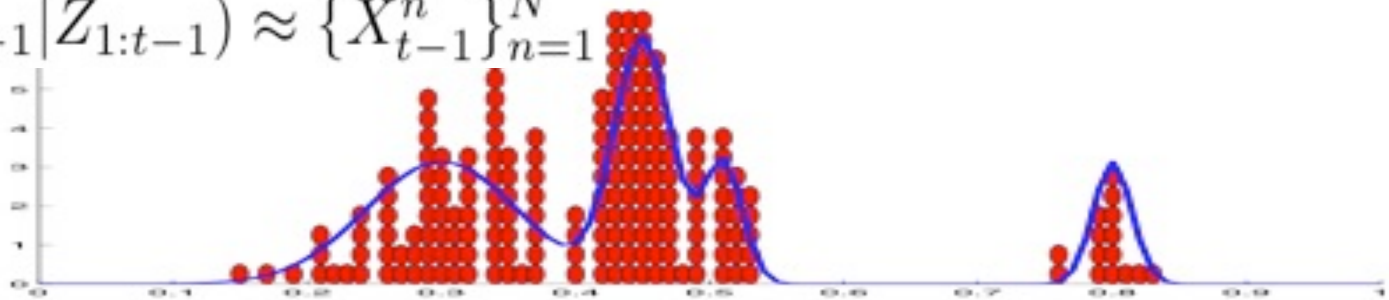

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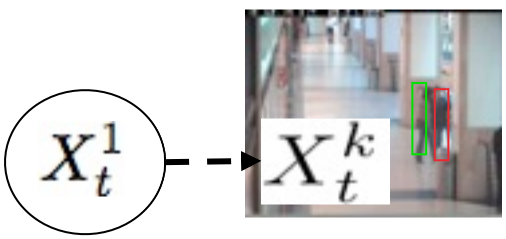

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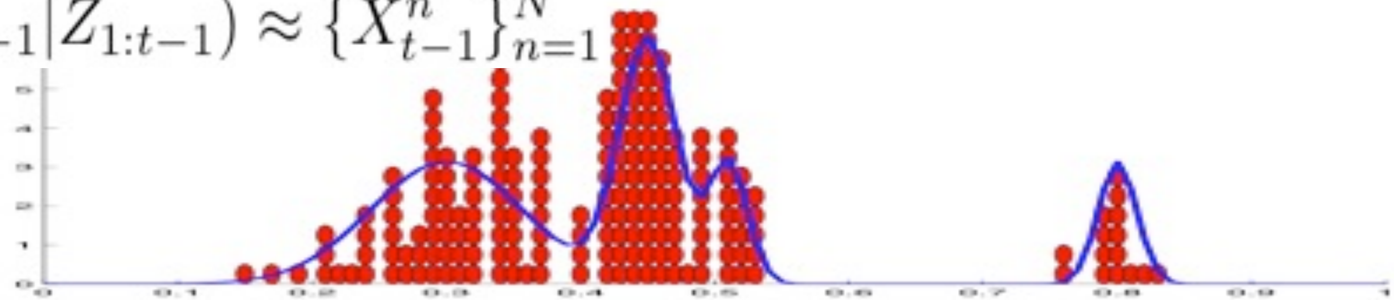
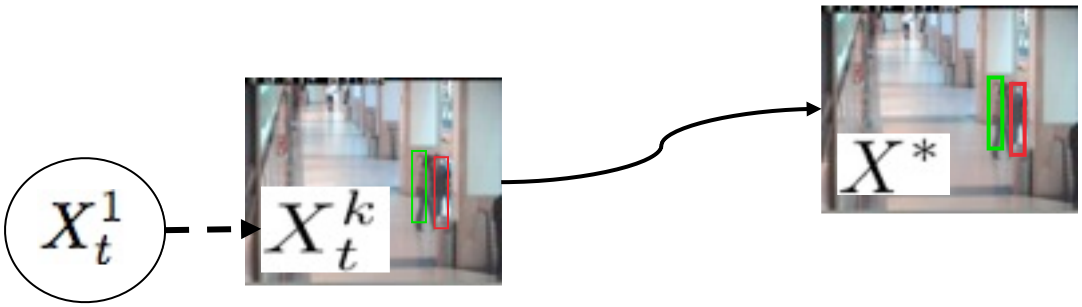


Metropolis Hasting rule



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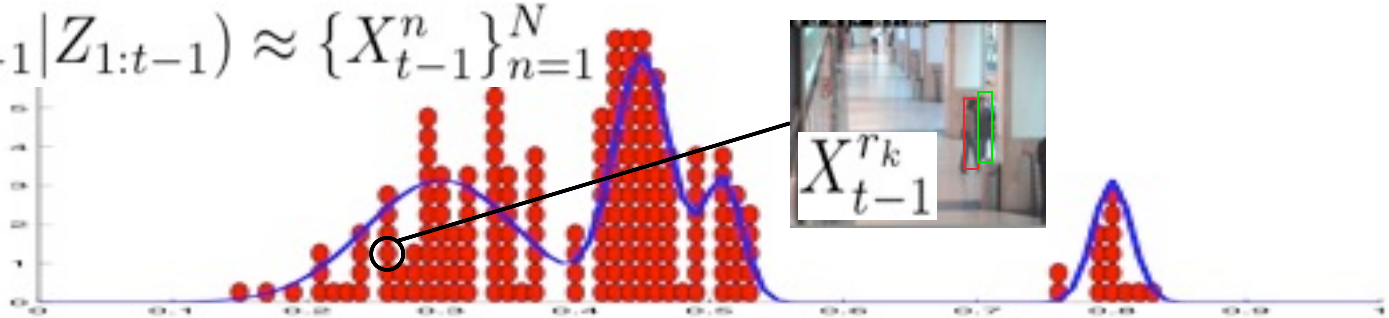
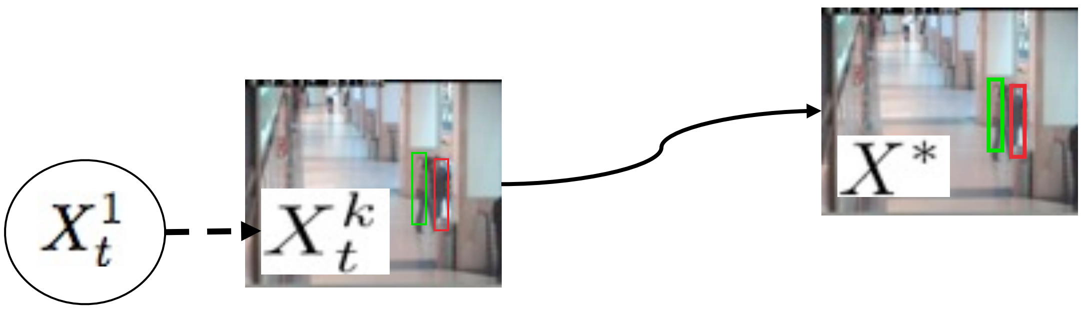
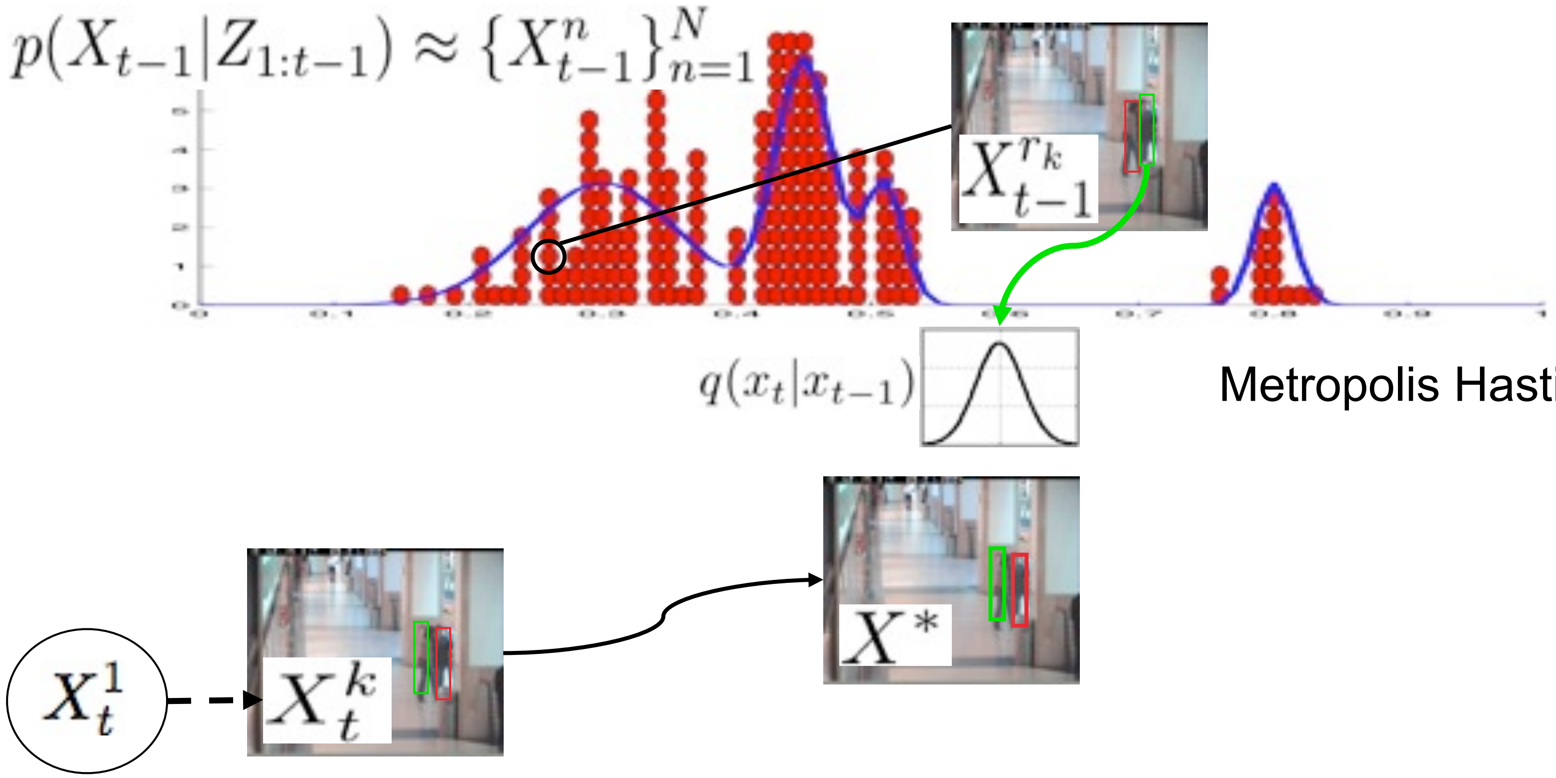


Metropolis Hasting rule



MCMC Particle Filter: marginal move



Metropolis Hasting rule

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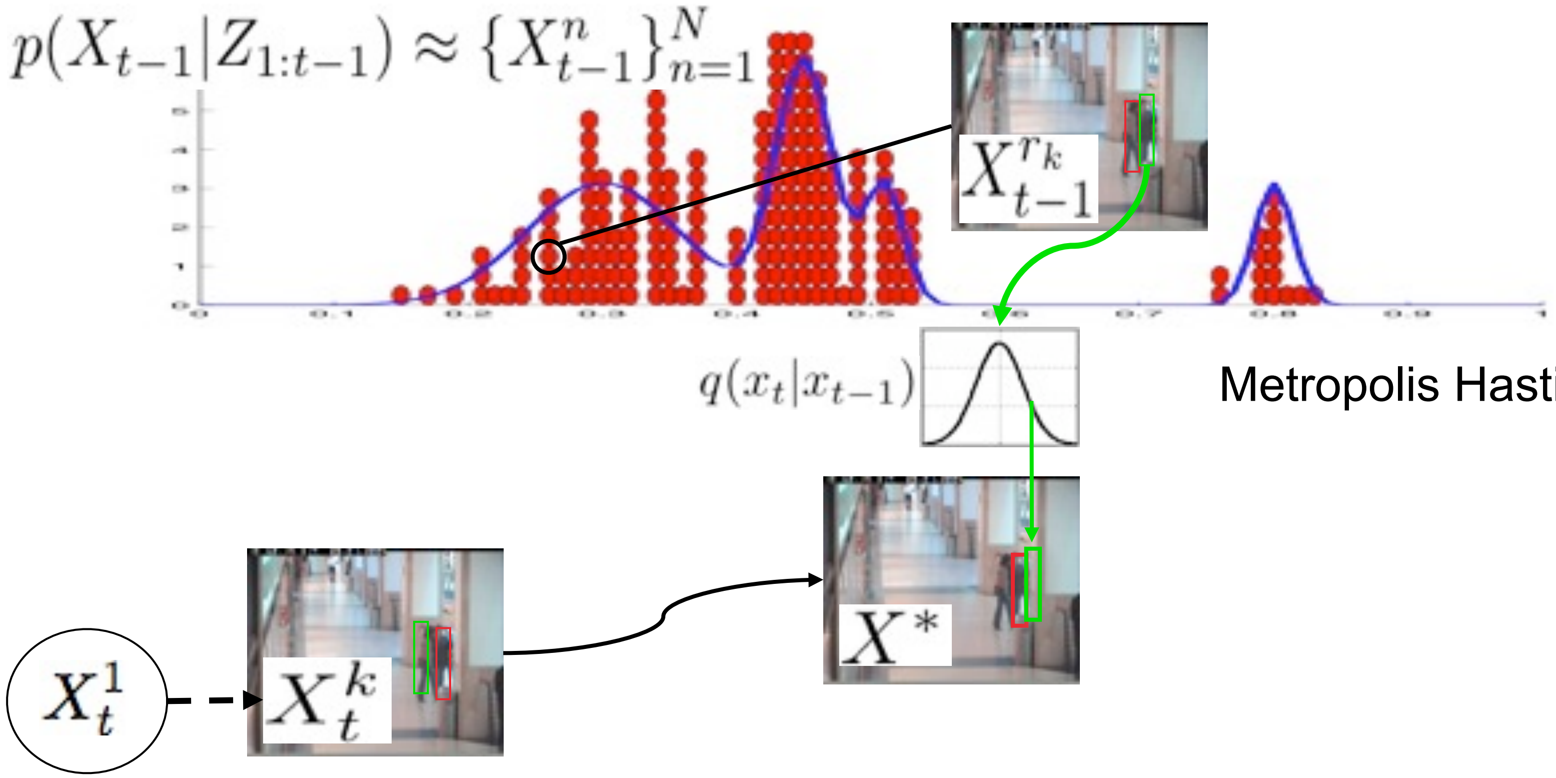
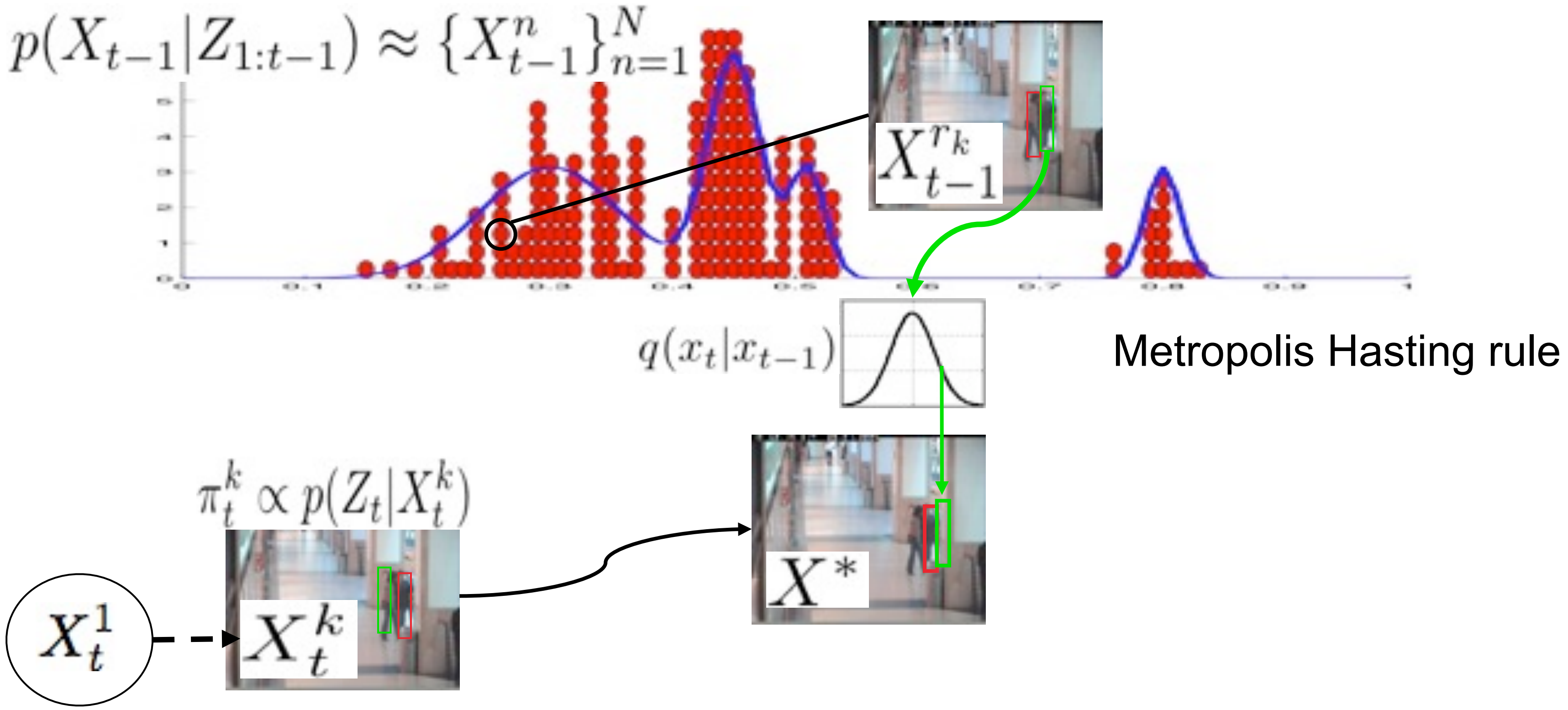
MCMC Particle Filter: marginal move



Metropolis Hasting rule

MCMC Particle Filter: marginal move



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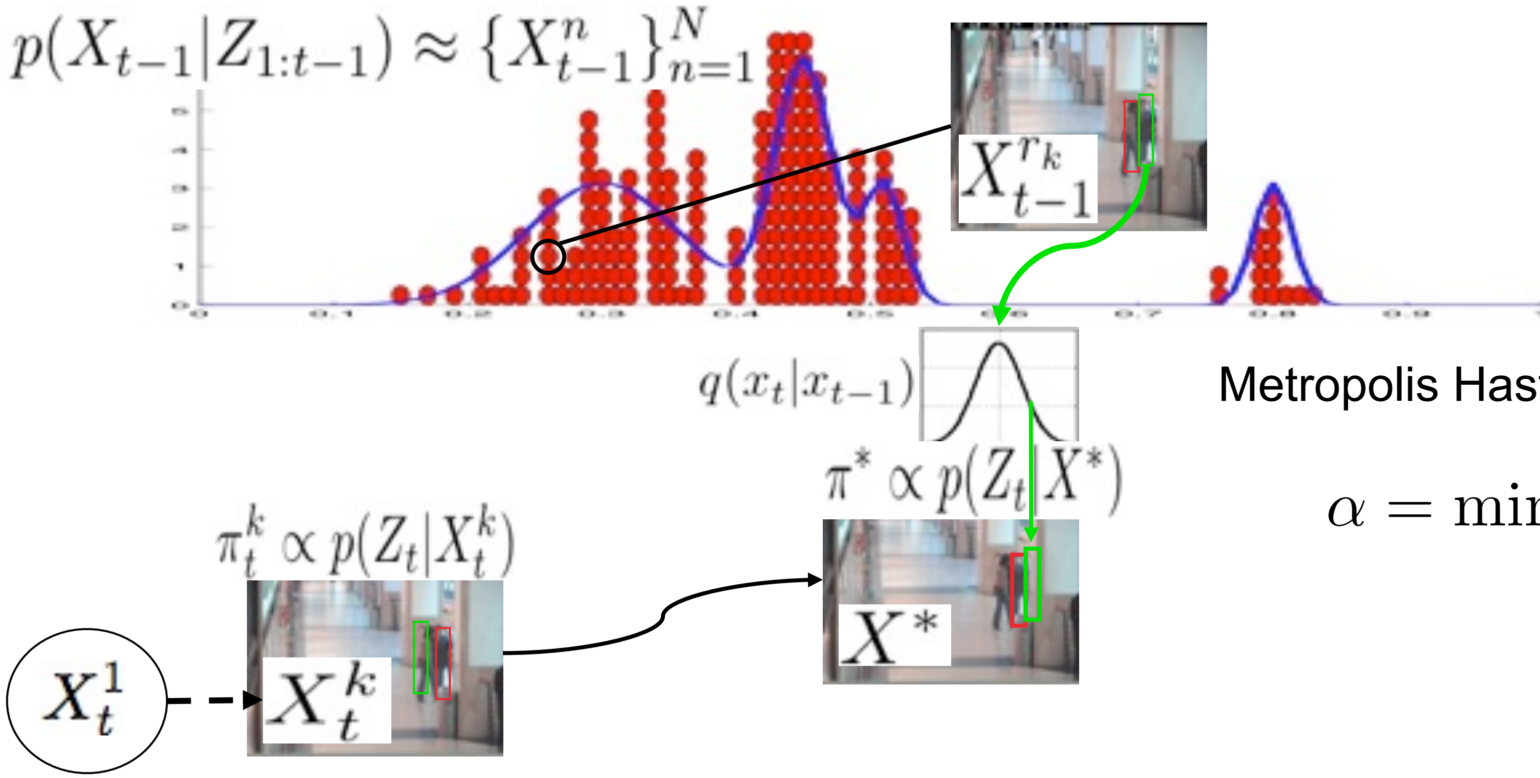
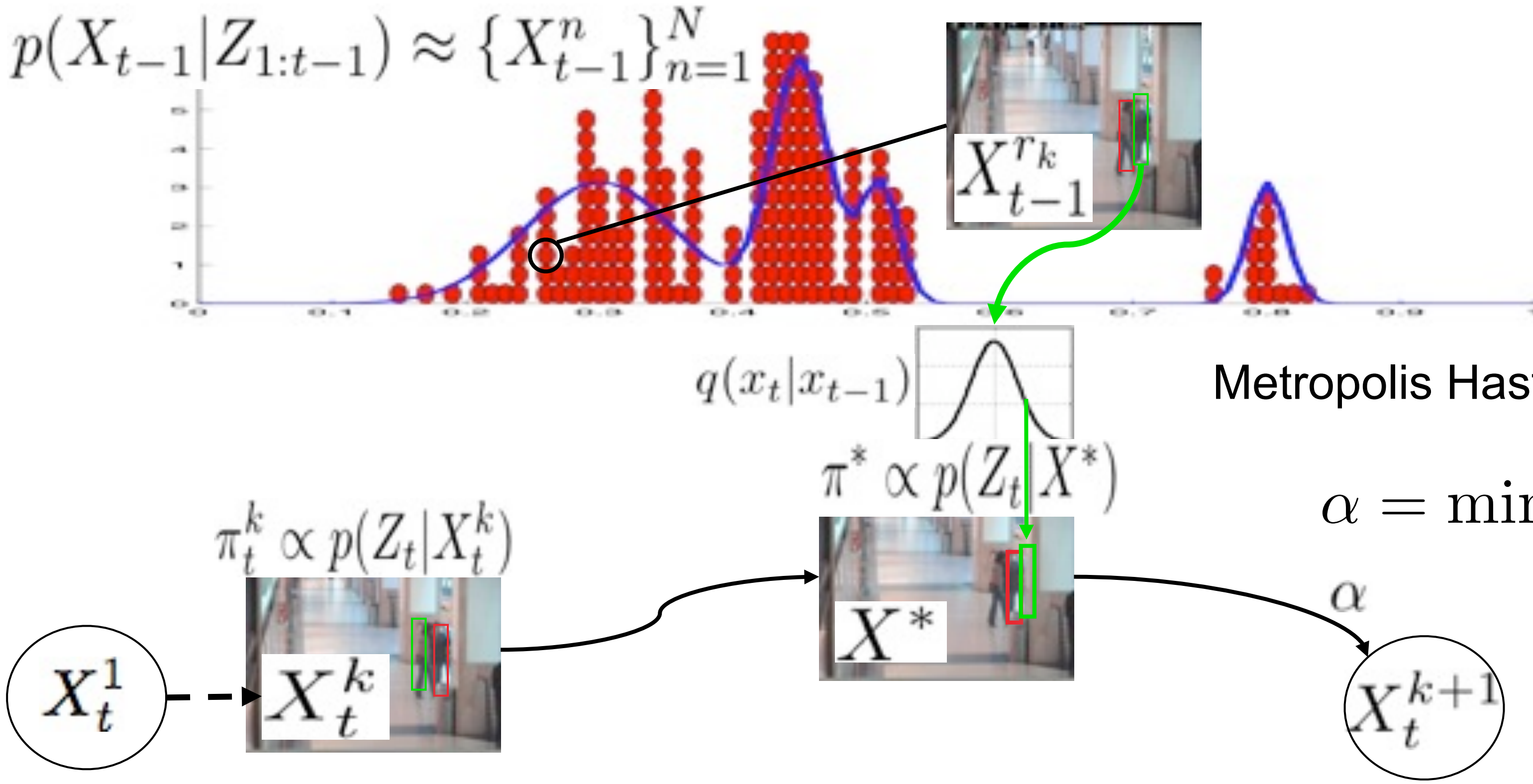
MCMC Particle Filter: marginal move



Metropolis Hasting rule

$$\alpha = \min\left(1, \frac{\pi^* \dots}{\pi_t^k \dots}\right)$$

MCMC Particle Filter: marginal move



Metropolis Hasting rule

$$\alpha = \min\left(1, \frac{\pi^* \ldots}{\pi_t^k \ldots}\right)$$

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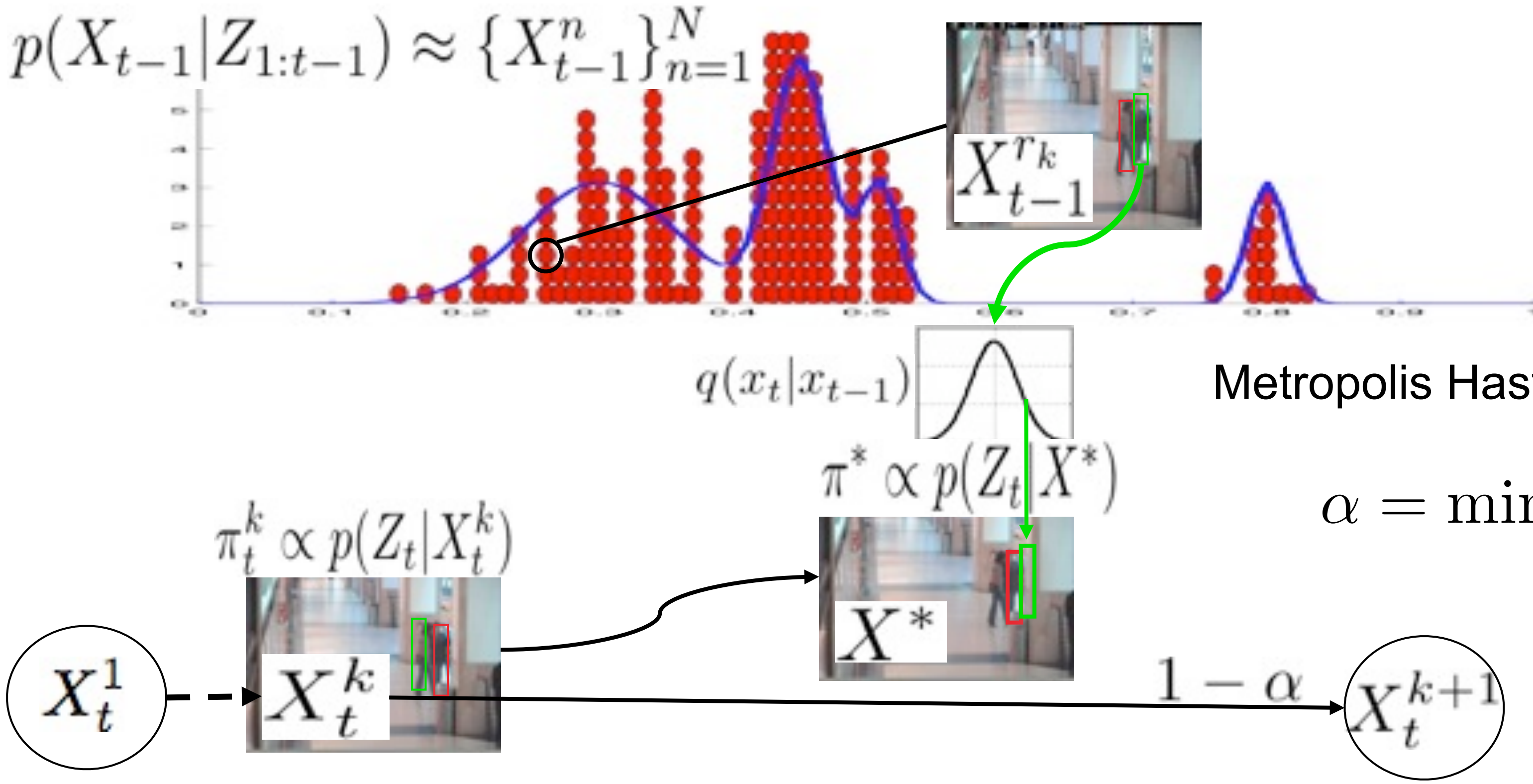
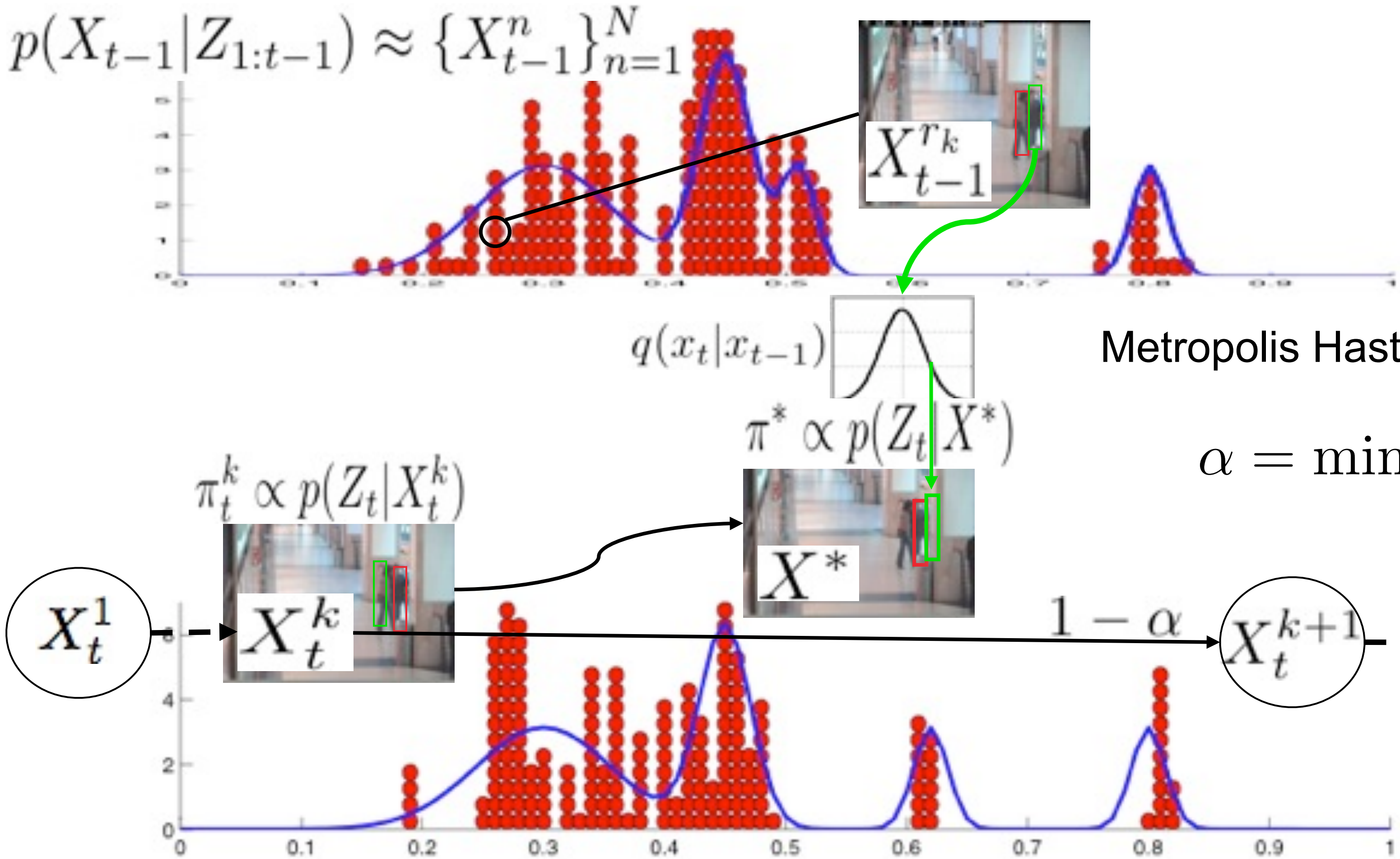
MCMC Particle Filter: marginal move



Metropolis Hasting rule

$$\alpha = \min\left(1, \frac{\pi^* \dots}{\pi_t^k \dots}\right)$$

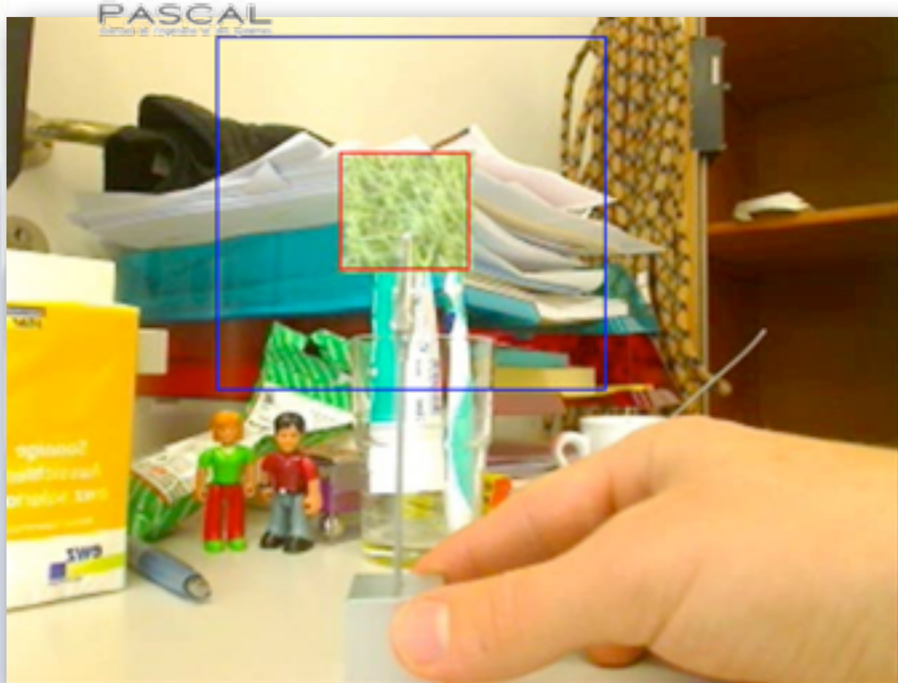
MCMC Particle Filter: marginal move

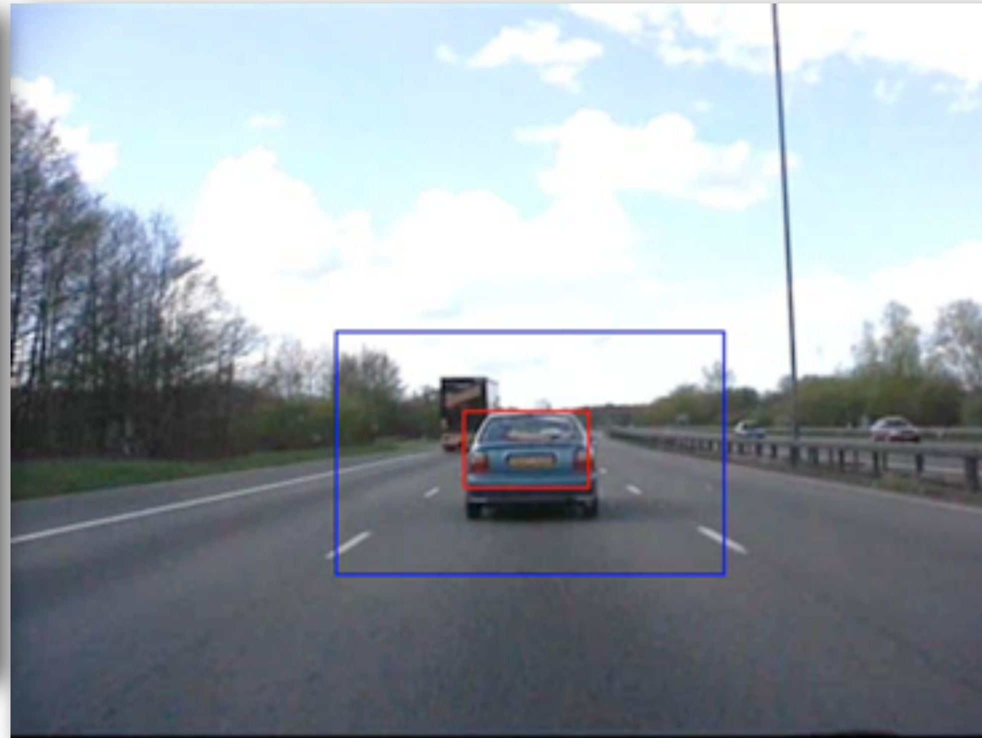


Metropolis Hasting rule

$$\alpha = \min\left(1, \frac{\pi^* \ldots}{\pi_t^k \ldots}\right)$$

MCMC Particle Filter: example





- State vector: 2D location, scale and combination parameters of observation modules (colour, texture, gradient, ...)
- Dynamics: random step
- Observation function: learning based (Adaboost)
- In collaboration with Teb-online

RJMCMC Particle Filter

Used to track a varying number of objects

$$\mathbf{X}_t \doteq \{I_t, \mathbf{x}_t^1, ..., \mathbf{x}_t^{I_t}\}$$

The state is defined into a joint space

RJMCMC Particle Filter

Reversible Jump Markov Chain Monte Carlo

Approximate the distribution with a variable size

A pair of new proposals

$$\mathbf{X} = \{x_1, x_2\}$$

Jump into a lower dimensional space

$$\mathbf{X} = \{x_1, x_2, x_3\}$$

$$\mathbf{X} = \{x_1, x_2, x_3, x_4\}$$

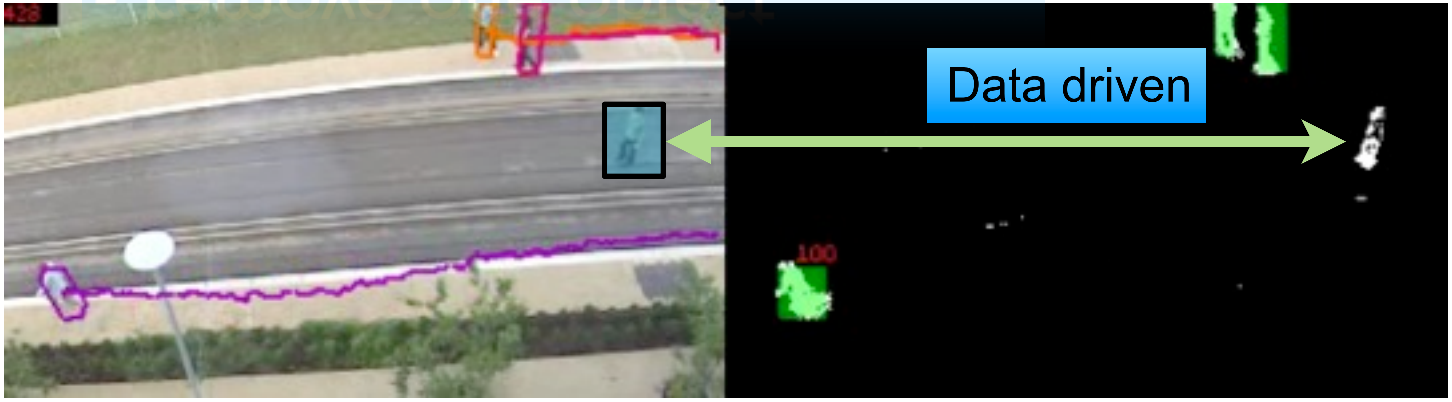
Jump into a higher dimensional space

RJMCMC Particle Filter

Proposals have to be add:

- object position update
- add one object
- remove one object

The state is defined into a joint space

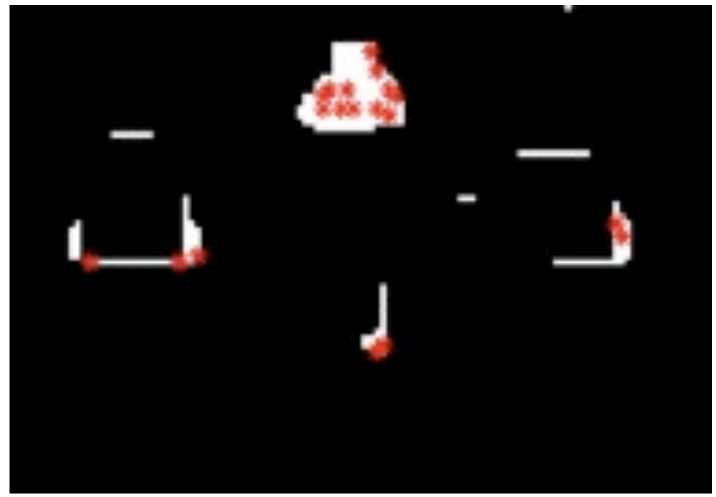


RJMCMC Particle Filter

Add an object: a data driven proposal

Background/foreground hypothesis

$\mathbf{X}^*$



New object position proposal map

Background/foreground observation map

RJMCMC Particle Filter

Real time pedestrian tracking

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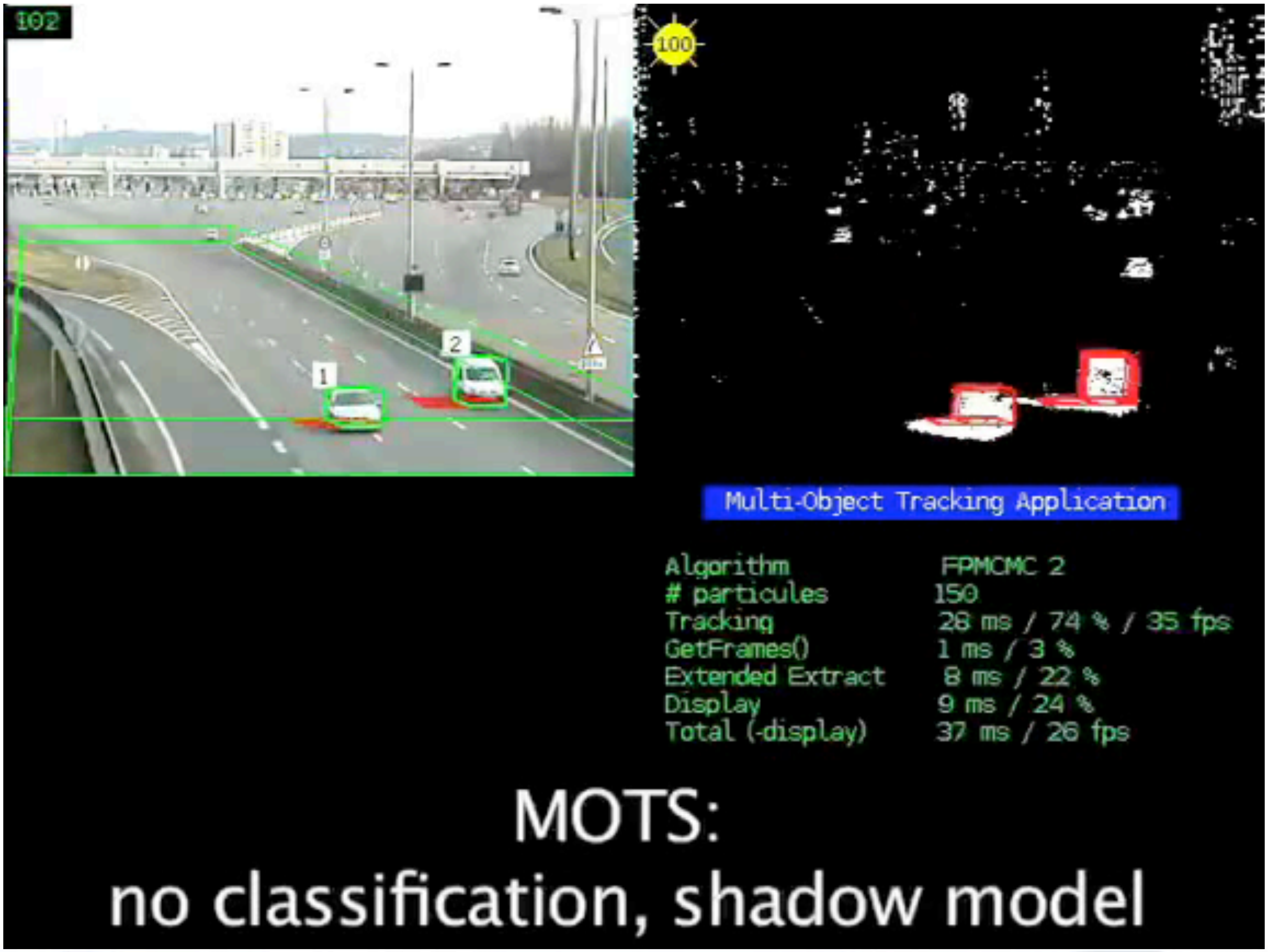
RJMCMC Particle Filter

Real time vehicle tracking

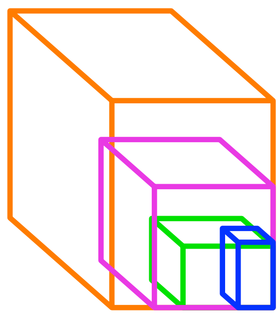


RJMCMC Particle Filter

Simultaneous tracking and categorisation

Proposals:

- update object position
- add/remove one object
- update object category



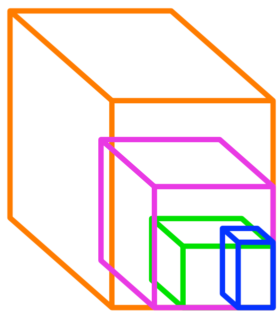
One geometric and kinematic model for each category

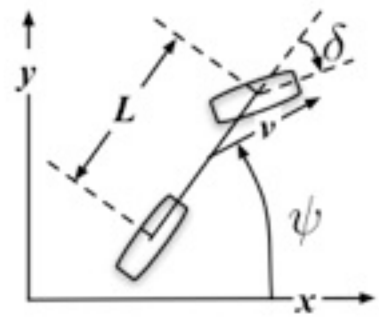
RJMCMC Particle Filter

Simultaneous tracking and categorisation

Proposals:

- update object position
- add/remove one object
- update object category





One geometric and kinematic model for each category

RJMCMC Particle Filter

Simultaneous tracking and categorisation

Proposals:

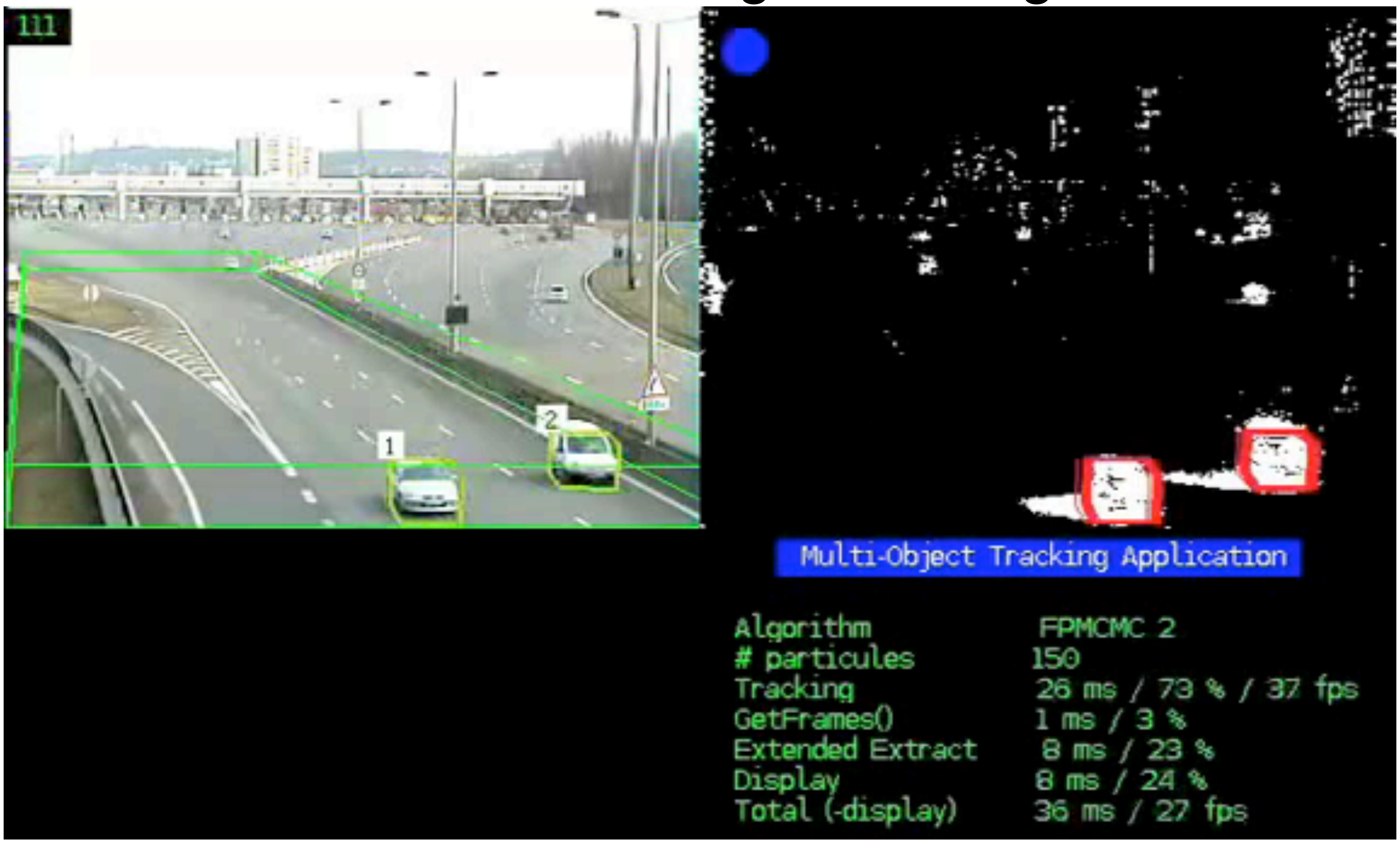
- update object position
- add/remove one object
- update object category

category update proposal matrix

$$\Theta = \begin{pmatrix} 1-2.t_c & 2.t_c & 0 & 0 \\ t_c & 1-2.t_c & t_c & 0 \\ 0 & t_c & 1-2.t_c & t_c \\ 0 & 0 & 2.t_c & 1-2.t_c \end{pmatrix}$$

RJMCMC Particle Filter

Simultaneous tracking and categorisation



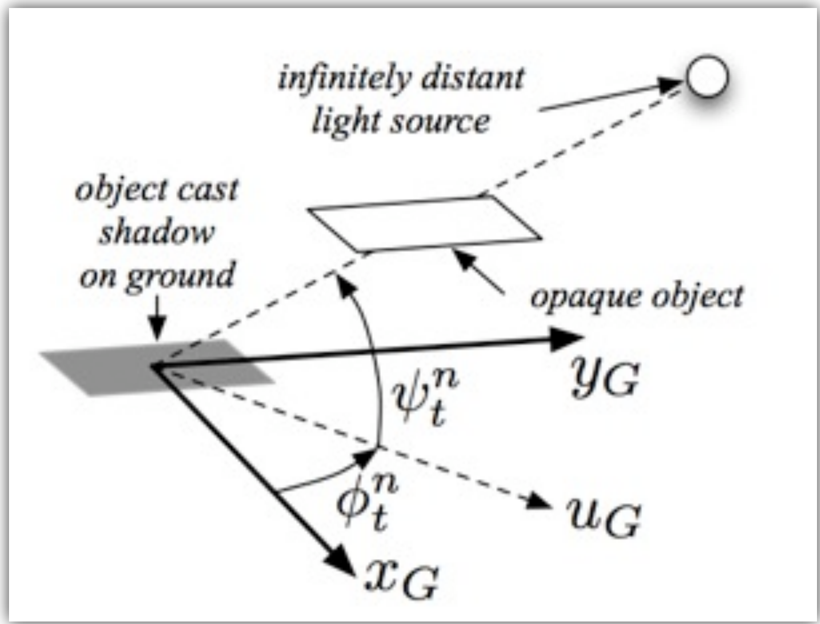
F. Bardet, T. Chateau, and D. Ramadasan. Unifying real-time multi-vehicle tracking and categorization. In *Intelligent Vehicle Symposium*, volume 1, 2009.

RJMCMC Particle Filter

Simultaneous tracking, categorisation and context detection

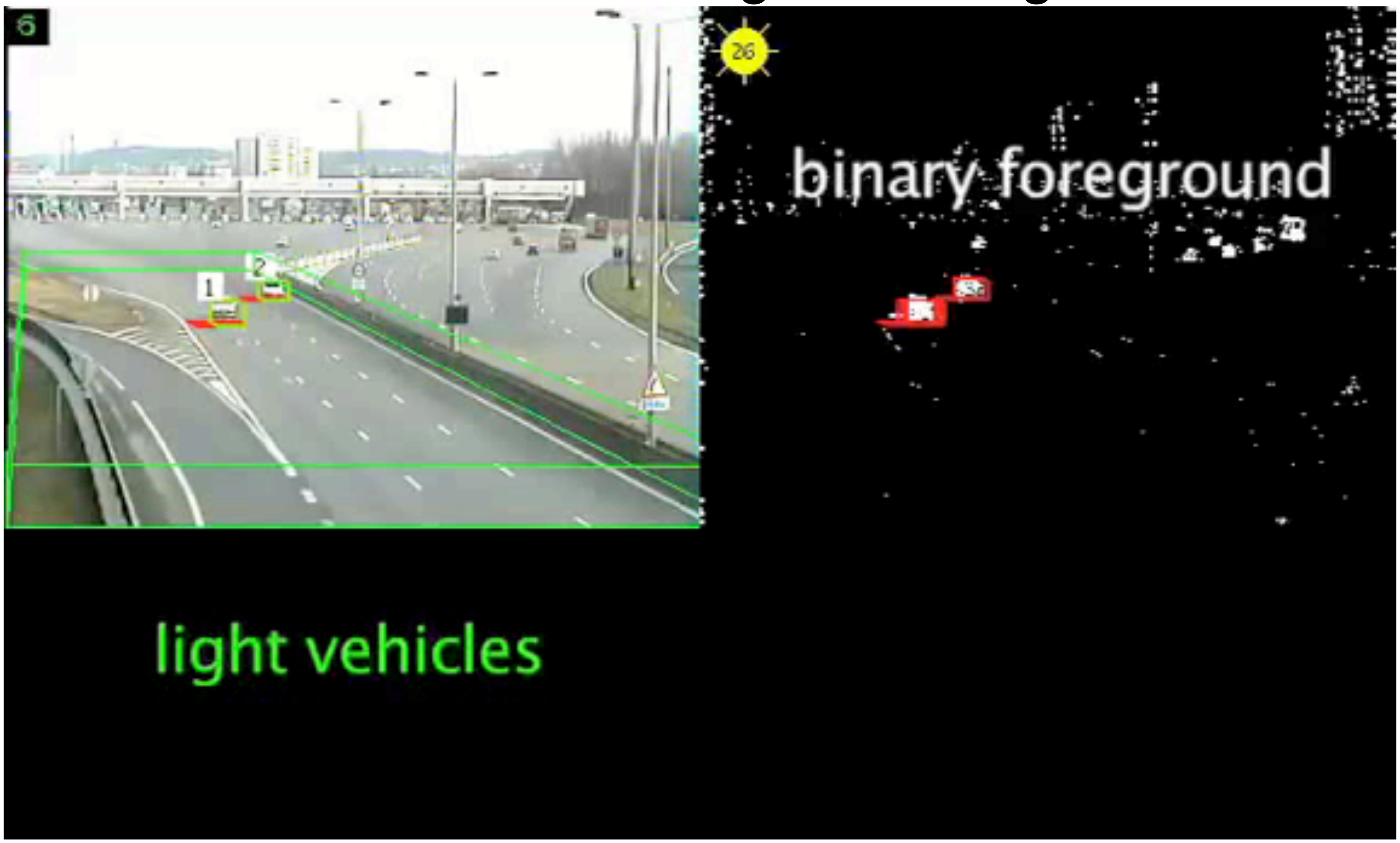
Proposals:

- update object or sun position position
- add/remove one object or sun
- update object category



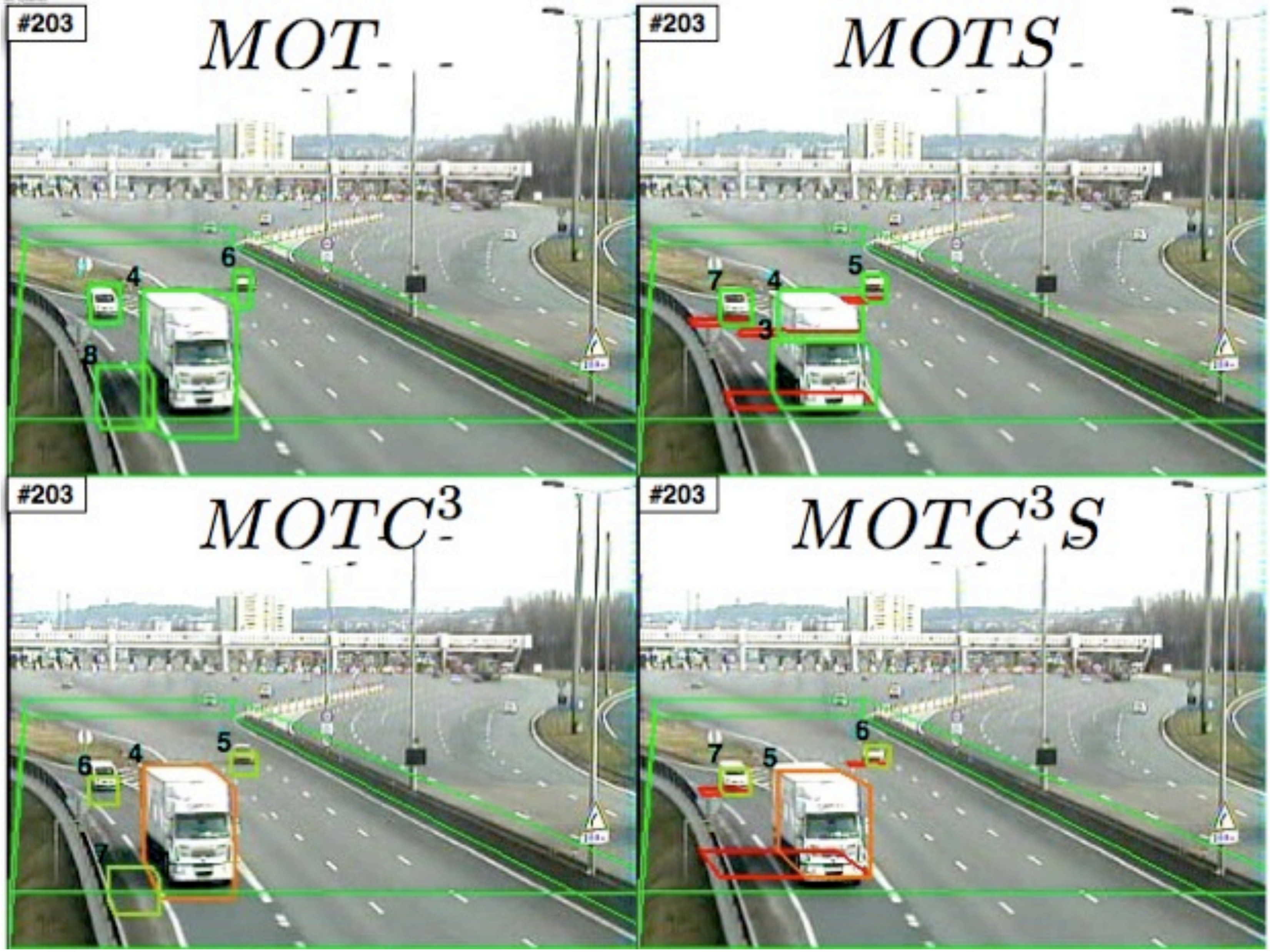
RJMCMC Particle Filter

Simultaneous tracking and categorisation



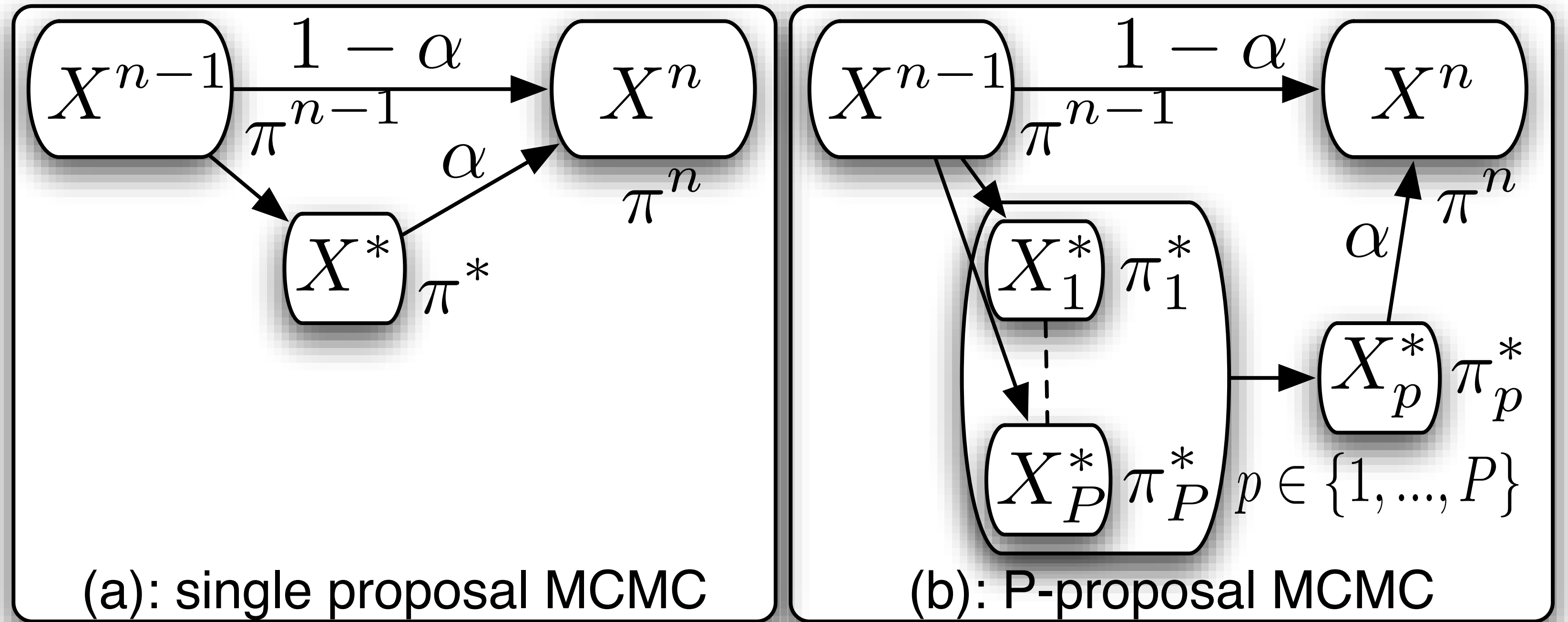
F. Bardet, T. Chateau, and J. Lapresté. Illumination aware mcmc particle filter for long-term outdoor multi-object simultaneous tracking and classification. In *ICCV 2009, International Conference on Computer Vision*, Tokyo, Japan, 09 2009.

RJMCMC Particle Filter



Efficient implementation of MCMC Particle Filters

Multi Proposal MCMC Particle Filter



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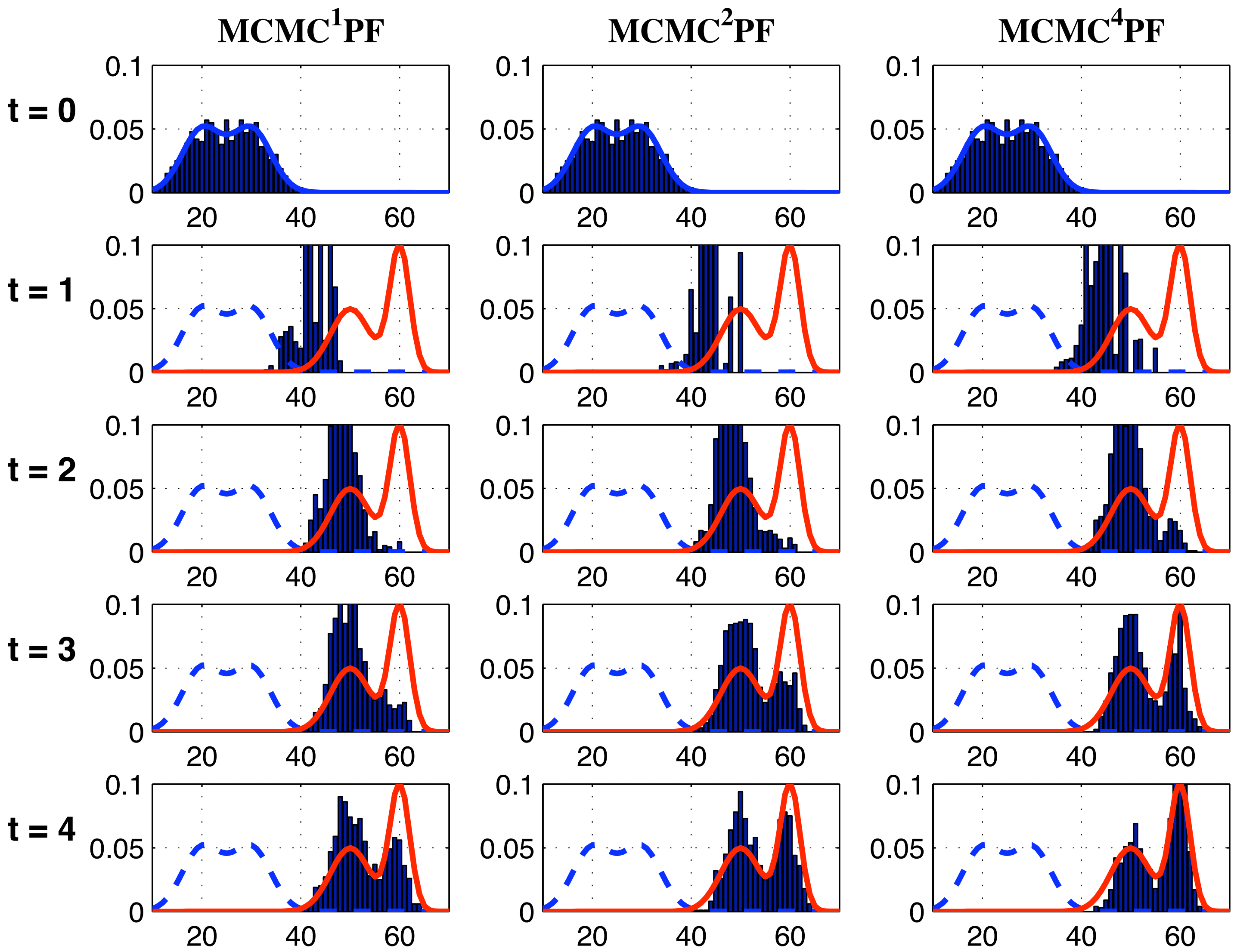
Efficient implementation of Particle Filters



Conclusion

- Particle filters are widely used for temporal filtering applications
- They provide tools able to handle with non linear systems
- SIR particle filters have to be chosen for low dimensional problems
- MCMC particle filters with marginal proposal strategy are preferred for high dimensional problems
- RJMCMC particle filters can be used to manage states with a varying dimension