

A two step hardware design method using CλaSH

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Contents

- ❖ Introduction
- ❖ Background
- ❖ Designing method applied to particle filter
- ❖ Results
- ❖ Conclusions & Future Work

Introduction

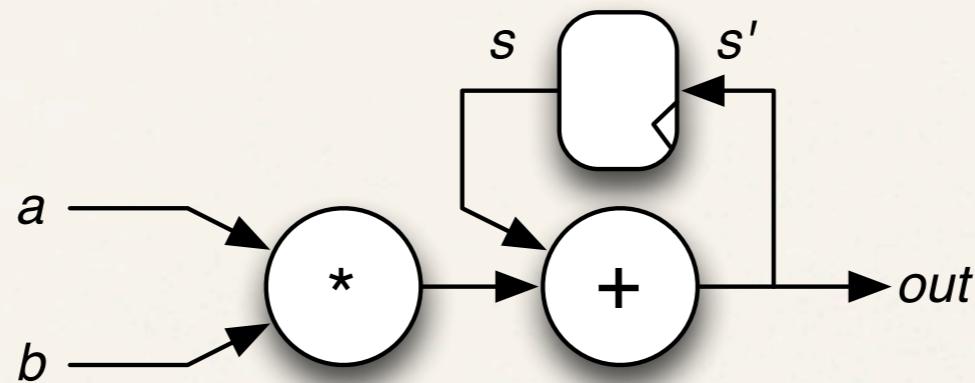
- ❖ What is C λ aSH?
 - ❖ Functional Language and Compiler for Concurrent Digital Hardware Design
- ❖ Motivation?
 - ❖ Evaluate C λ aSH and design method on complex application
- ❖ Why a particle filter?
 - ❖ Covers important aspects of digital hardware design: massive parallelism, feedback loop and data dependent processing.

Background

CλaSH

- ✿ CλaSH
 - ✿ A functional language and compiler for digital hardware design
 - ✿ On the lowest level, everything is a Mealy machine $f(s,i) = (s',o)$
 - ✿ A CλaSH description is purely structural i.e. all operations are performed in a single clock cycle
 - ✿ Simulation is cycle accurate

Background



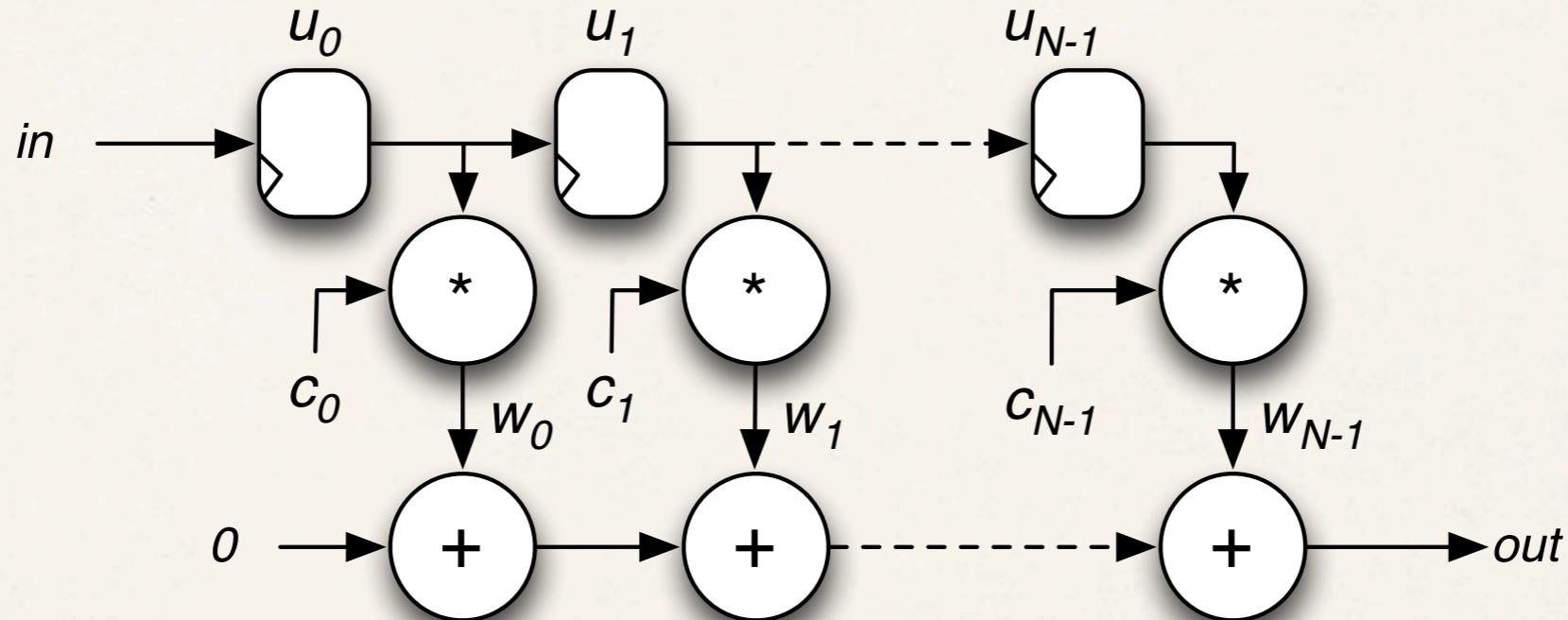
$mac (State\ s)\ (a, b) = (State\ s', out)$

where

$$s' = s + a * b$$

$$out = s'$$

Background



fir cs (State us) inp = (State us', out)

where

$$us' = inp \ggg us$$

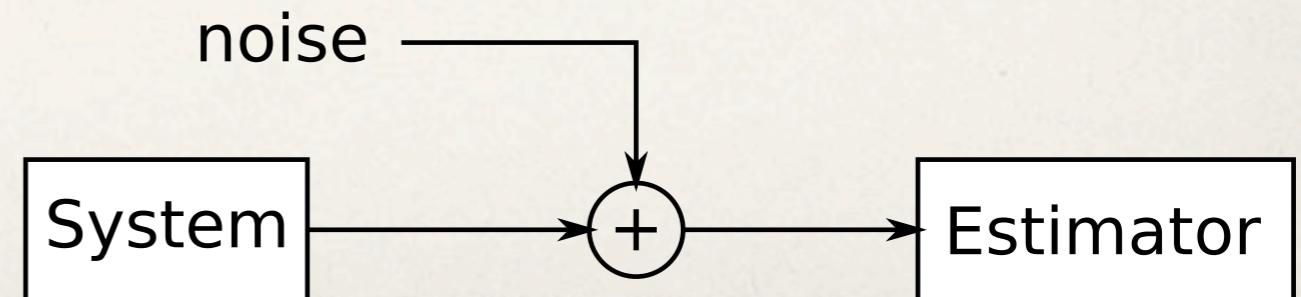
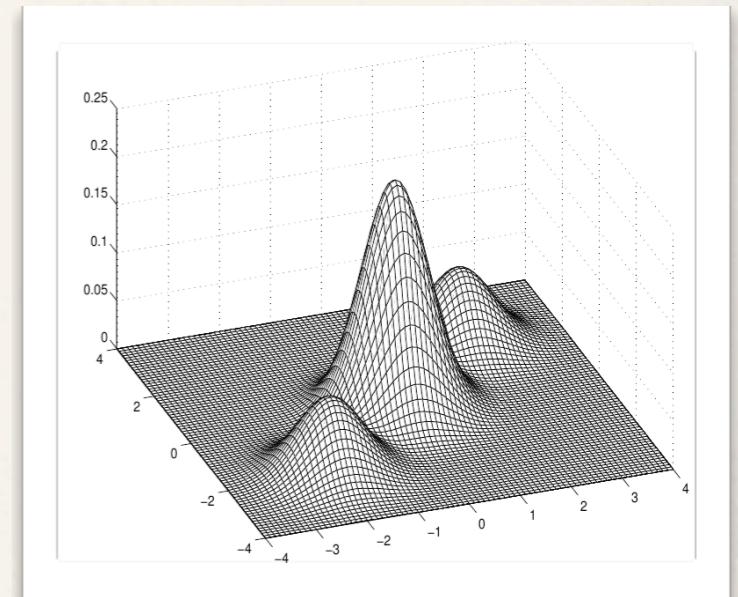
$$ws = vzipWith (*) us cs$$

$$out = vfoldl (+) 0 ws$$

Background

State estimation

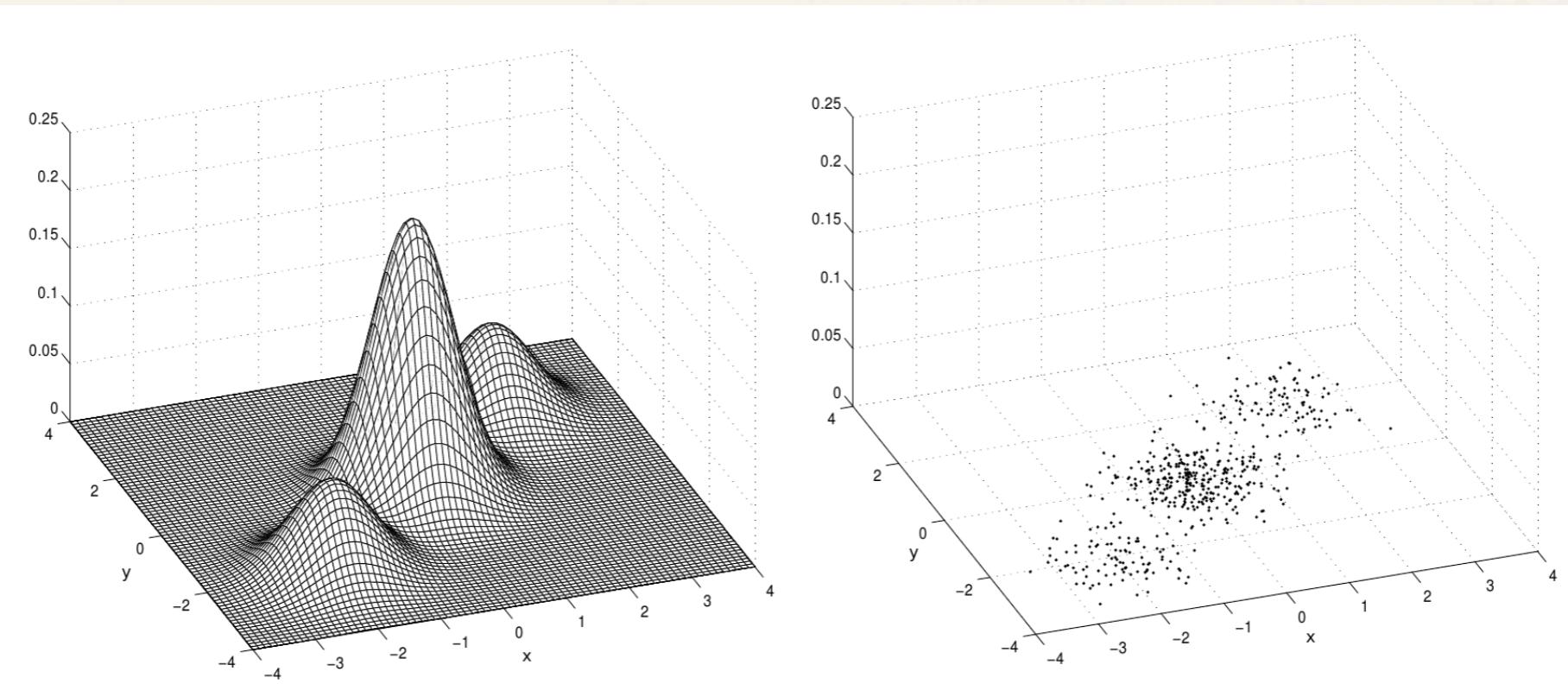
- ❖ State estimation
 - ❖ Determine $p(x_k | z_k)$ recursively with noise
 - ❖ State variables: position, speed, angle, ...
 - ❖ Applications: tracking in radar and video
- ❖ Requirements for estimator
 - ❖ System dynamics
 - ❖ Measurement function



Background

Particle Filter

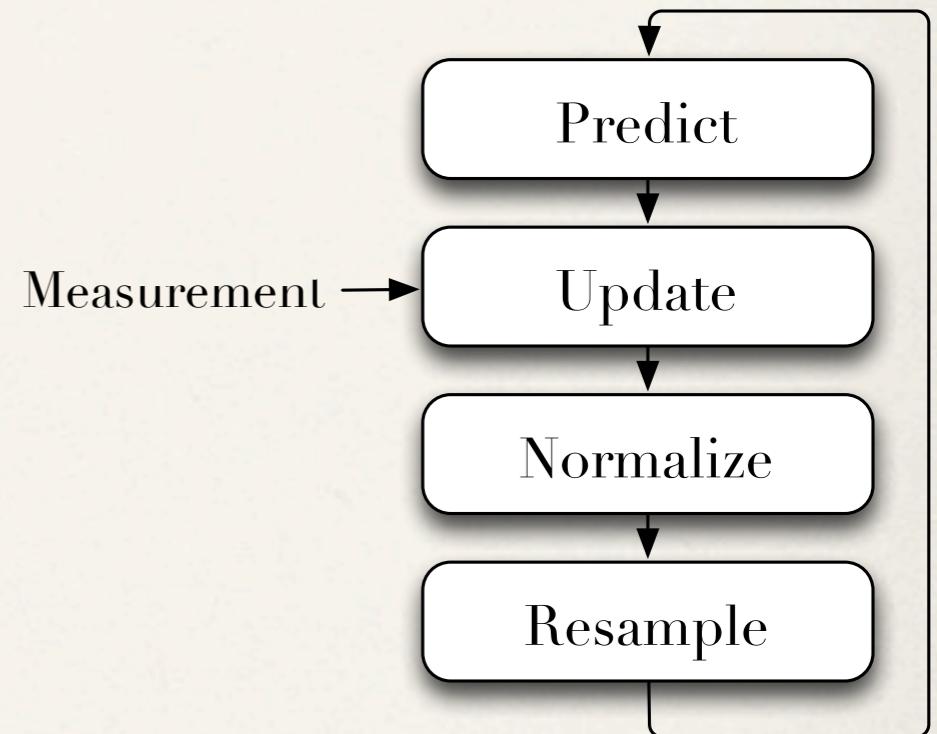
- Monte Carlo approximation of $p(x_k | z_k)$ represented by concentration of points (particles)
- Applicable to non-linear, non gaussian systems (tracking, robotics,..)
- Parameterizable in and N , $F_{sys}(x)$ and $F_{meas}(x,m)$



Background

Particle Filter

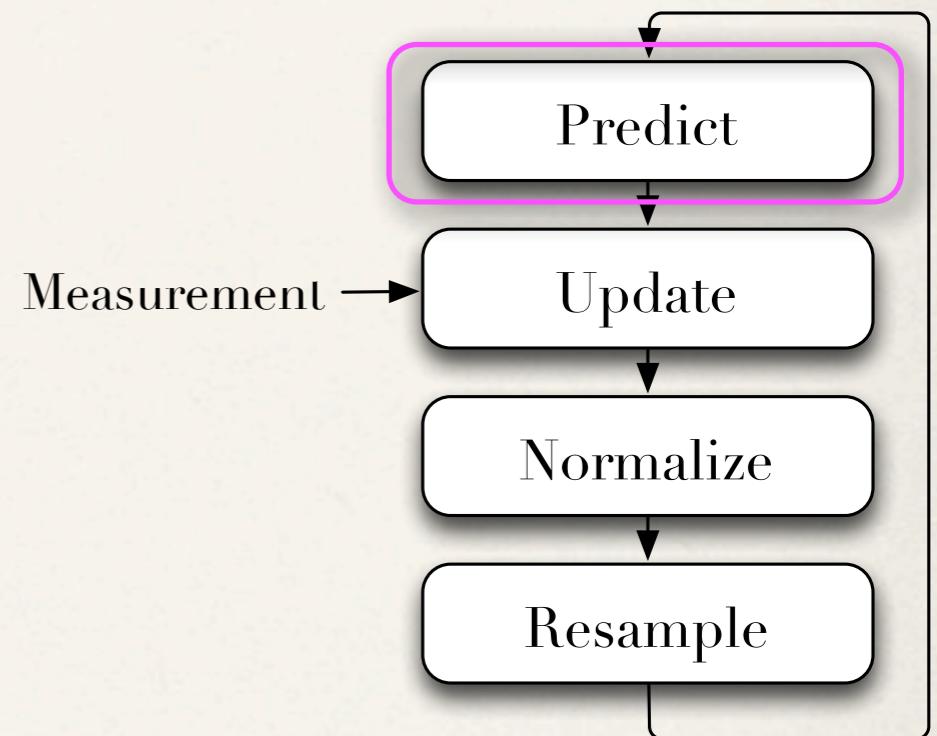
- * Prediction
 - * Predict next state based on current $F_{sys}(x) \rightarrow x'$
- * Update
 - * Assign weights to particles based on measurement $F_{meas}(x,m) \rightarrow \omega$
- * Normalize such that $\sum \omega^{(i)}=1$
- * Resample



Background

Particle Filter

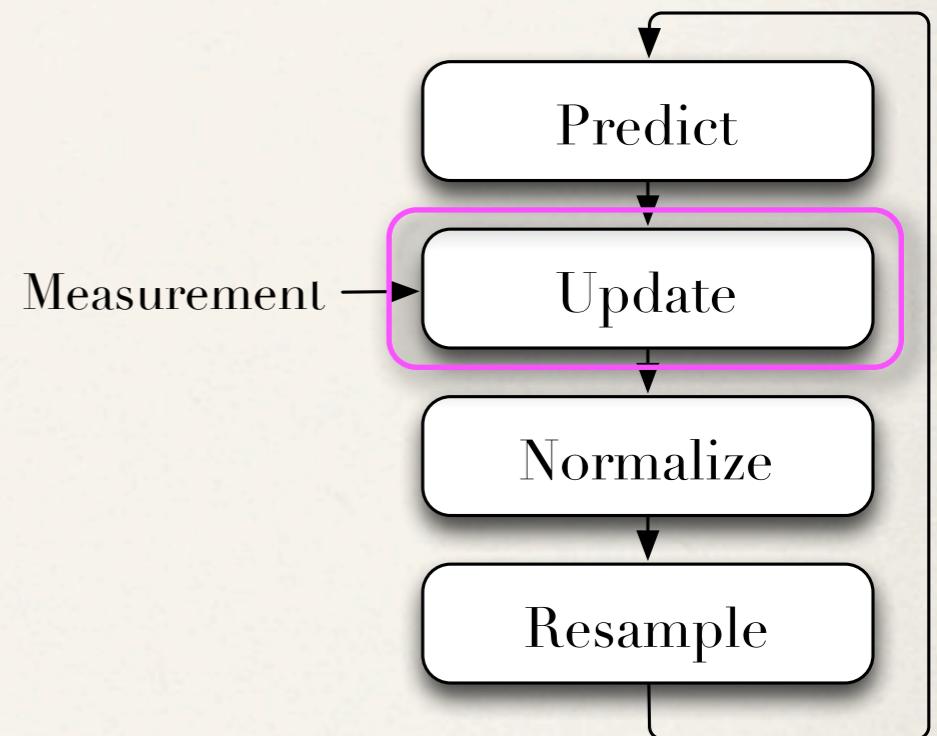
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Particle Filter

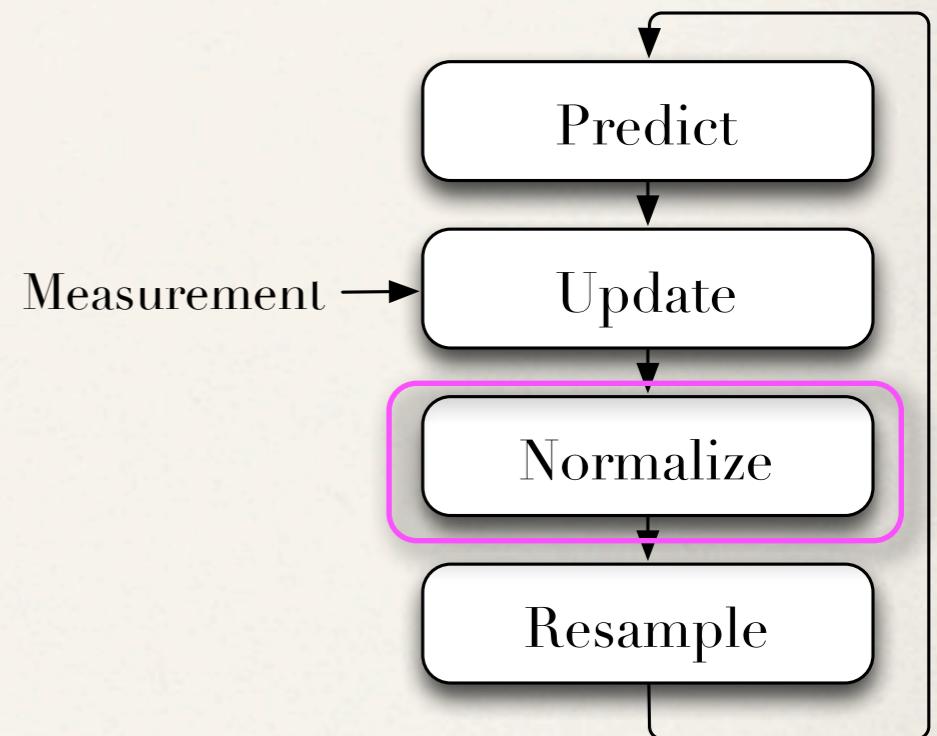
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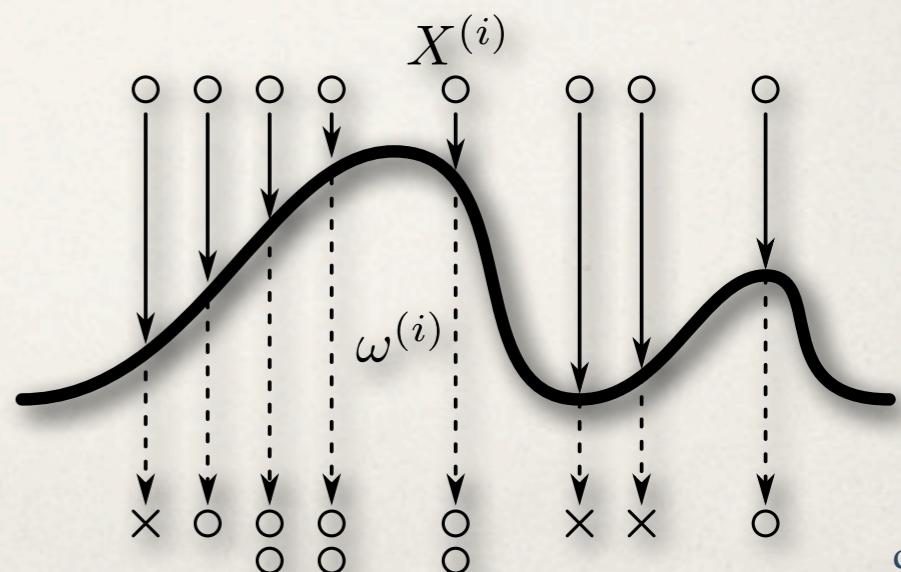
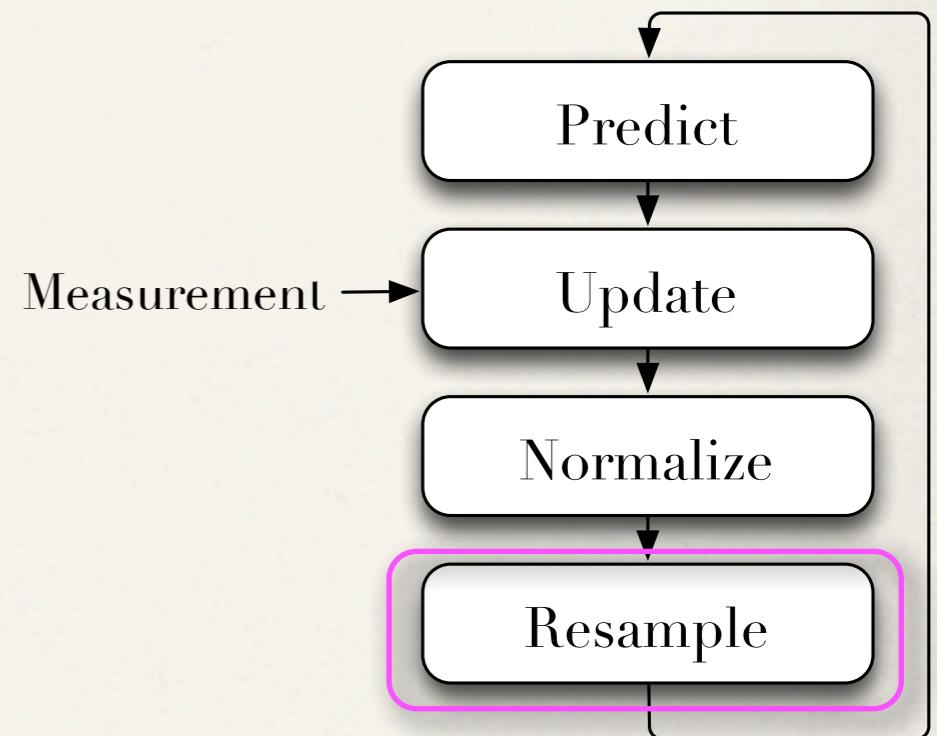
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Background

Mathematical formulation of Particle Filter

* Prediction

$$x_k^{(i)} \sim p(x_k | x_{k-1})$$

* System dynamics function

$$x_k^{(i)} = f(x_{k-1}^{(i)}, u_k)$$

* Update

$$\omega_k^{(i)} = p(z_k | x_k^{(i)})$$

* Measurement function

$$\omega_k^{(i)} = g(x_k^{(i)}, z_k, v_k), \quad \text{for } i = 1 \dots N$$

* Normalize

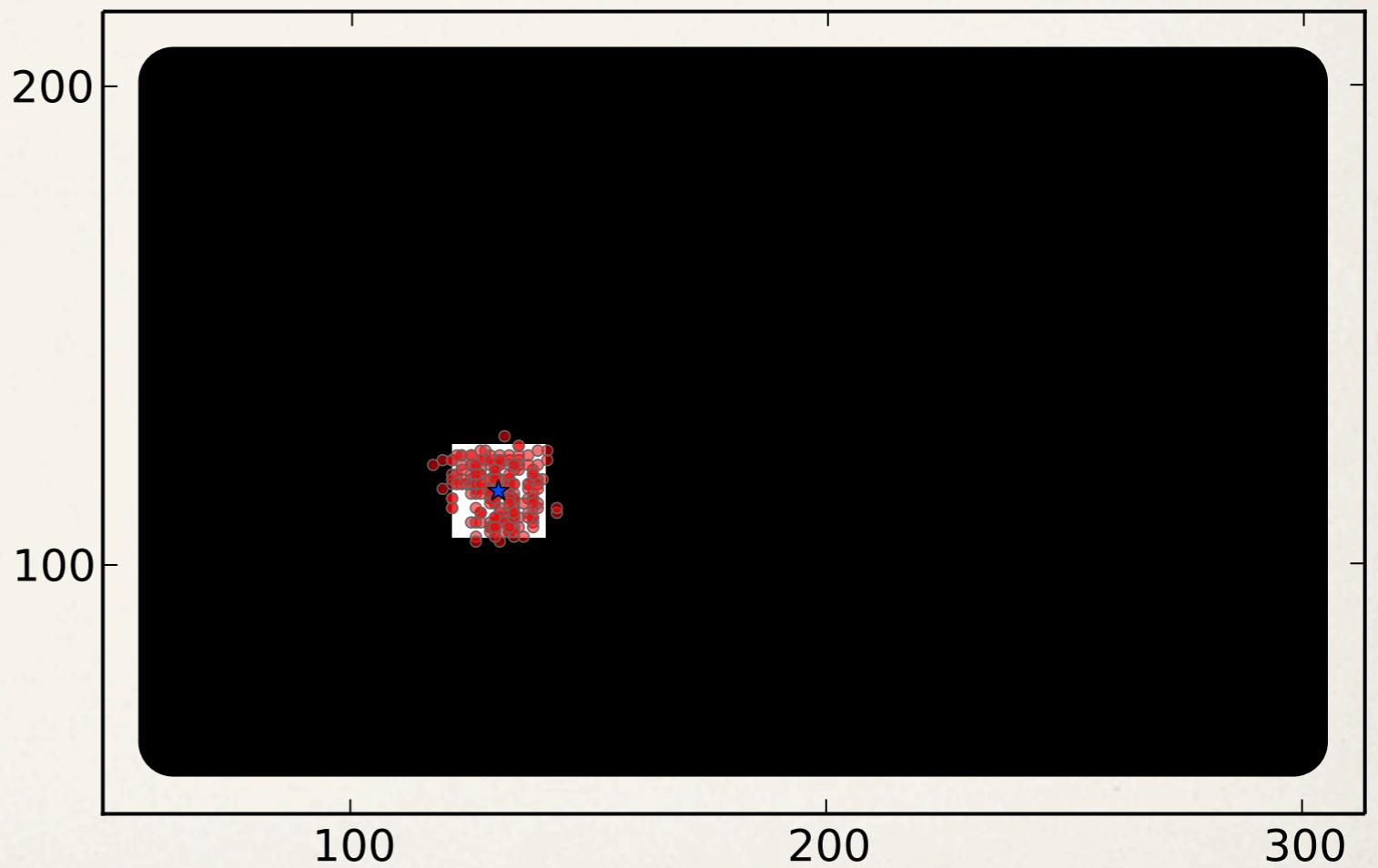
$$\tilde{\omega}^{(i)} = \frac{\omega^{(i)}}{\sum_{n=1}^N \omega^{(n)}} \quad \text{for } i = 1 \dots N$$

* Resample

$$\{\tilde{x}_k^{(1)}, \tilde{x}_k^{(2)}, \dots, \tilde{x}_k^{(N)}\} = \prod_{n=1}^N replicate(x_k^{(i)}, r_i)$$

Background

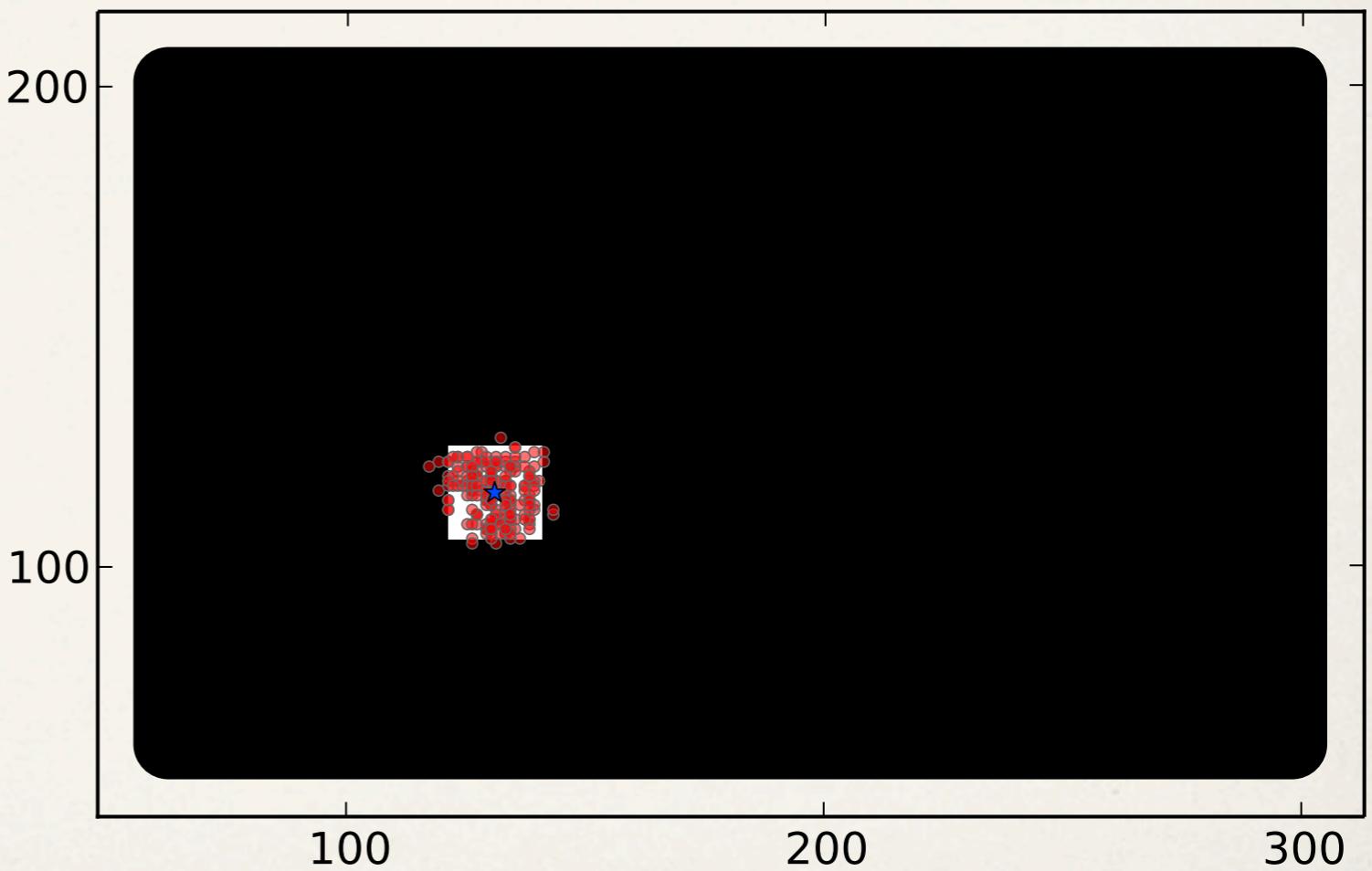
Simple tracking application



Background

Simple tracking application

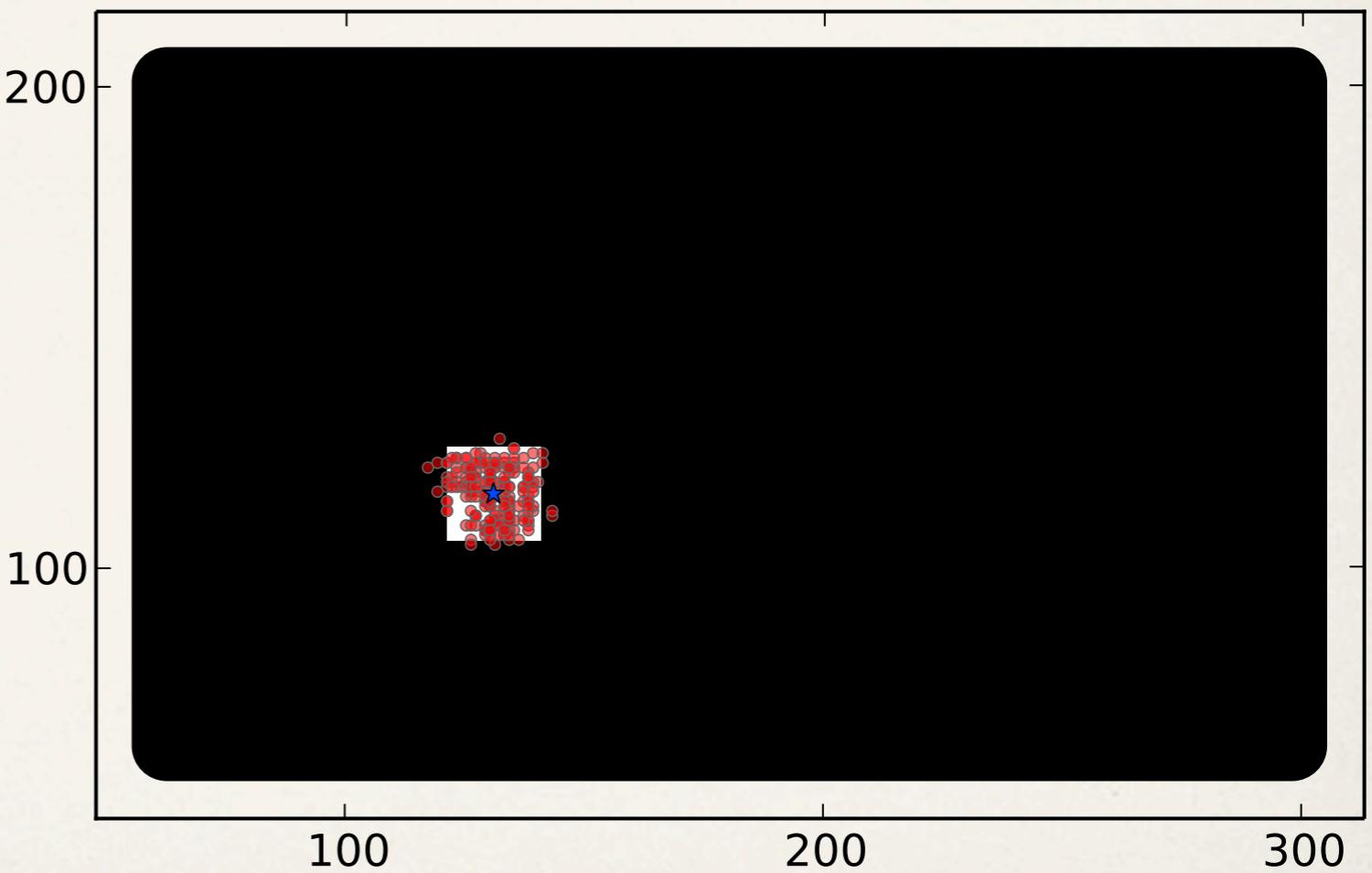
- ❖ Tracking a square on a dark background



Background

Simple tracking application

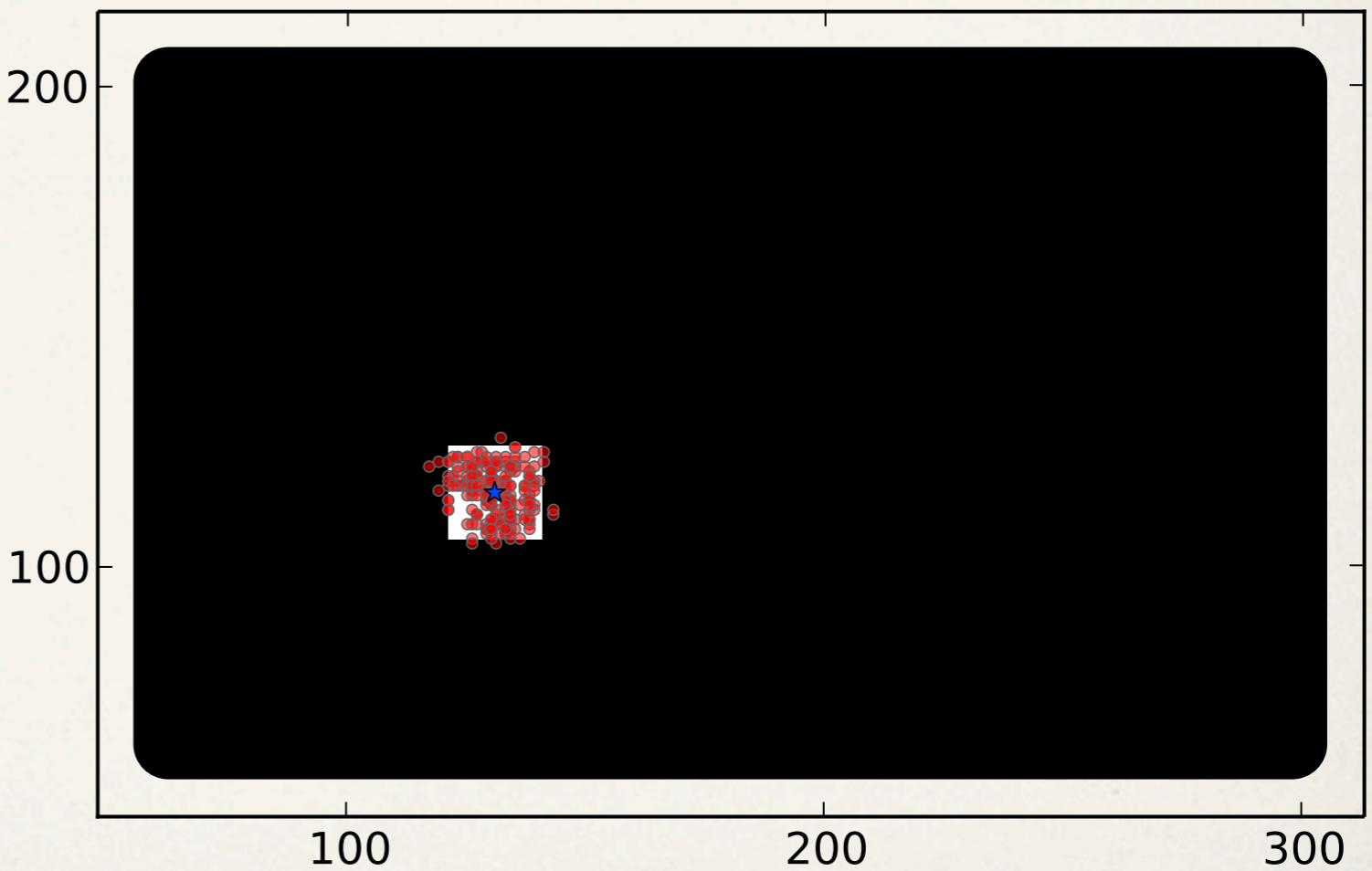
- ❖ Tracking a square on a dark background
- ❖ Particle: $X^{(i)} = \langle x, y, \omega \rangle$



Background

Simple tracking application

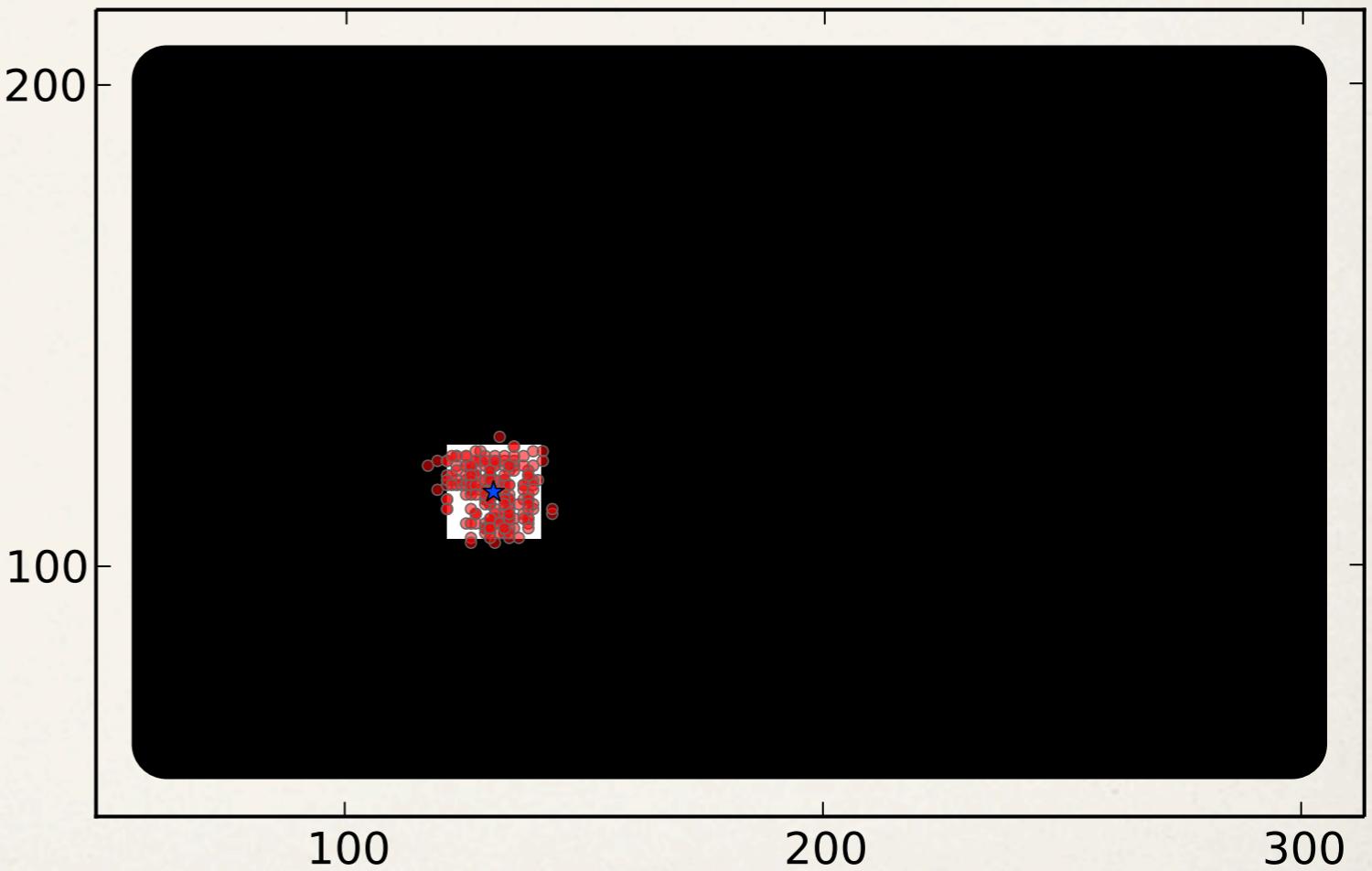
- ❖ Tracking a square on a dark background
 - ❖ Particle: $X^{(i)} = \langle x, y, \omega \rangle$
 - ❖ System dynamics



Background

Simple tracking application

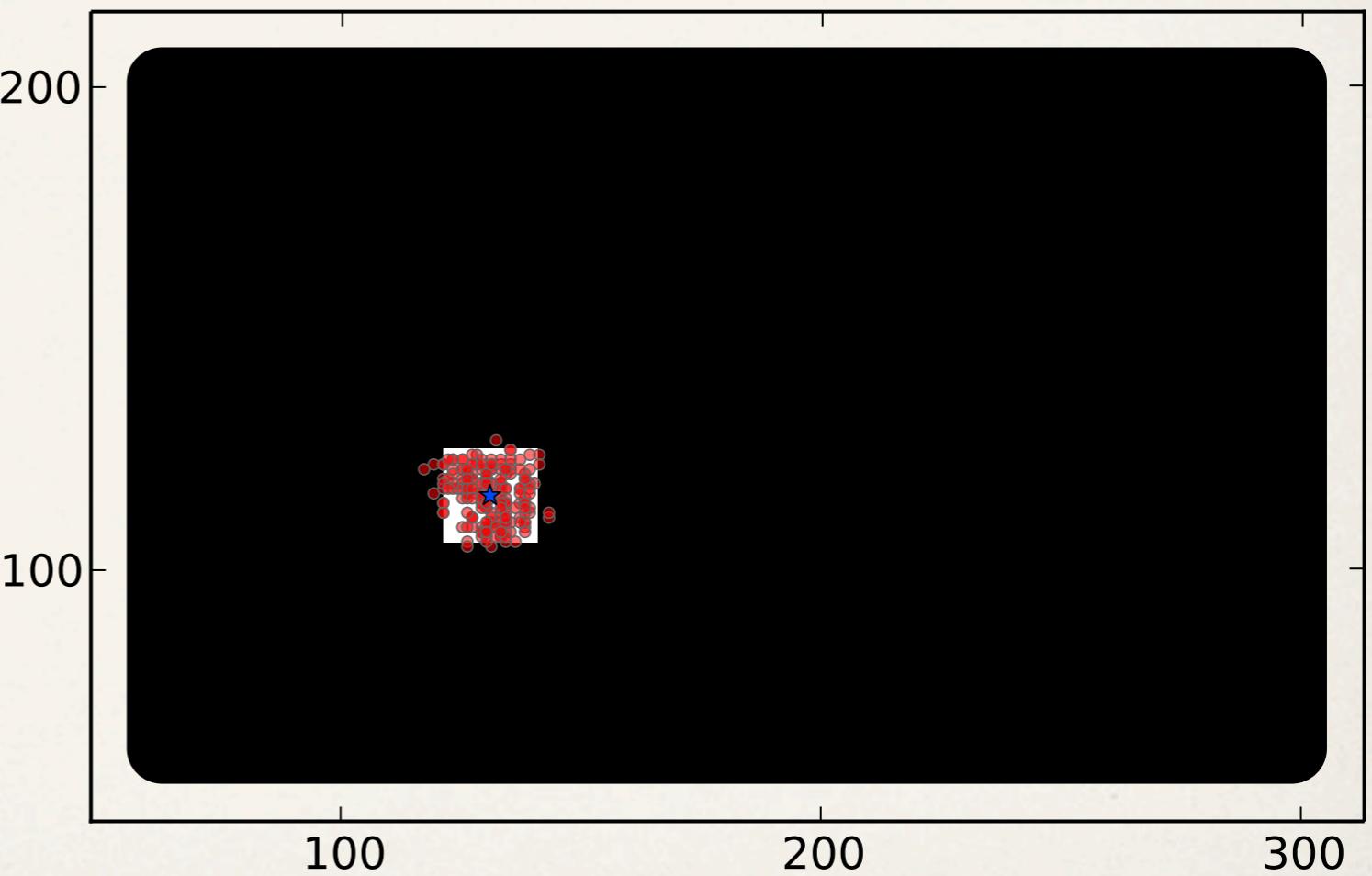
- Tracking a square on a dark background
 - Particle: $X^{(i)} = \langle x, y, \omega \rangle$
 - System dynamics
 - $(x', y') = (x + \delta_x, y + \delta_y)$ where $\delta_x, \delta_y \sim U(-a, a)$



Background

Simple tracking application

- ❖ Tracking a square on a dark background
 - ❖ Particle: $X^{(i)} = \langle x, y, \omega \rangle$
- ❖ System dynamics
 - ❖ $(x', y') = (x + \delta_x, y + \delta_y)$
where $\delta_x, \delta_y \sim U(-a, a)$
- ❖ Measurement function



Background

Simple tracking application

- Tracking a square on a dark background

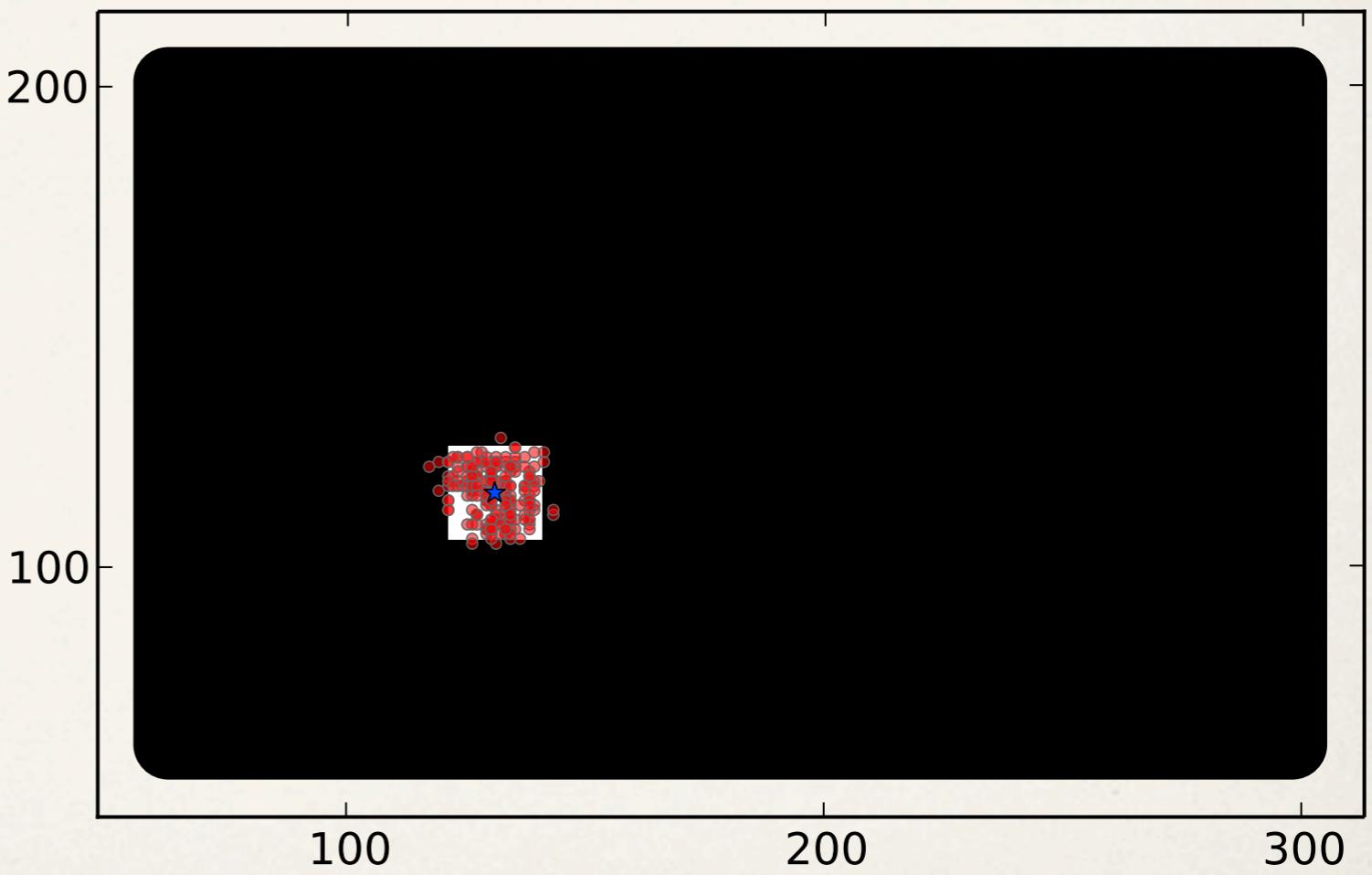
- Particle: $X^{(i)} = \langle x, y, \omega \rangle$

- System dynamics

- $(x', y') = (x + \delta_x, y + \delta_y)$
where $\delta_x, \delta_y \sim U(-a, a)$

- Measurement function

- $\omega = 1 / (1 + (255 - p_{xl})^2)$



Background

Simple tracking application

- Tracking a square on a dark background

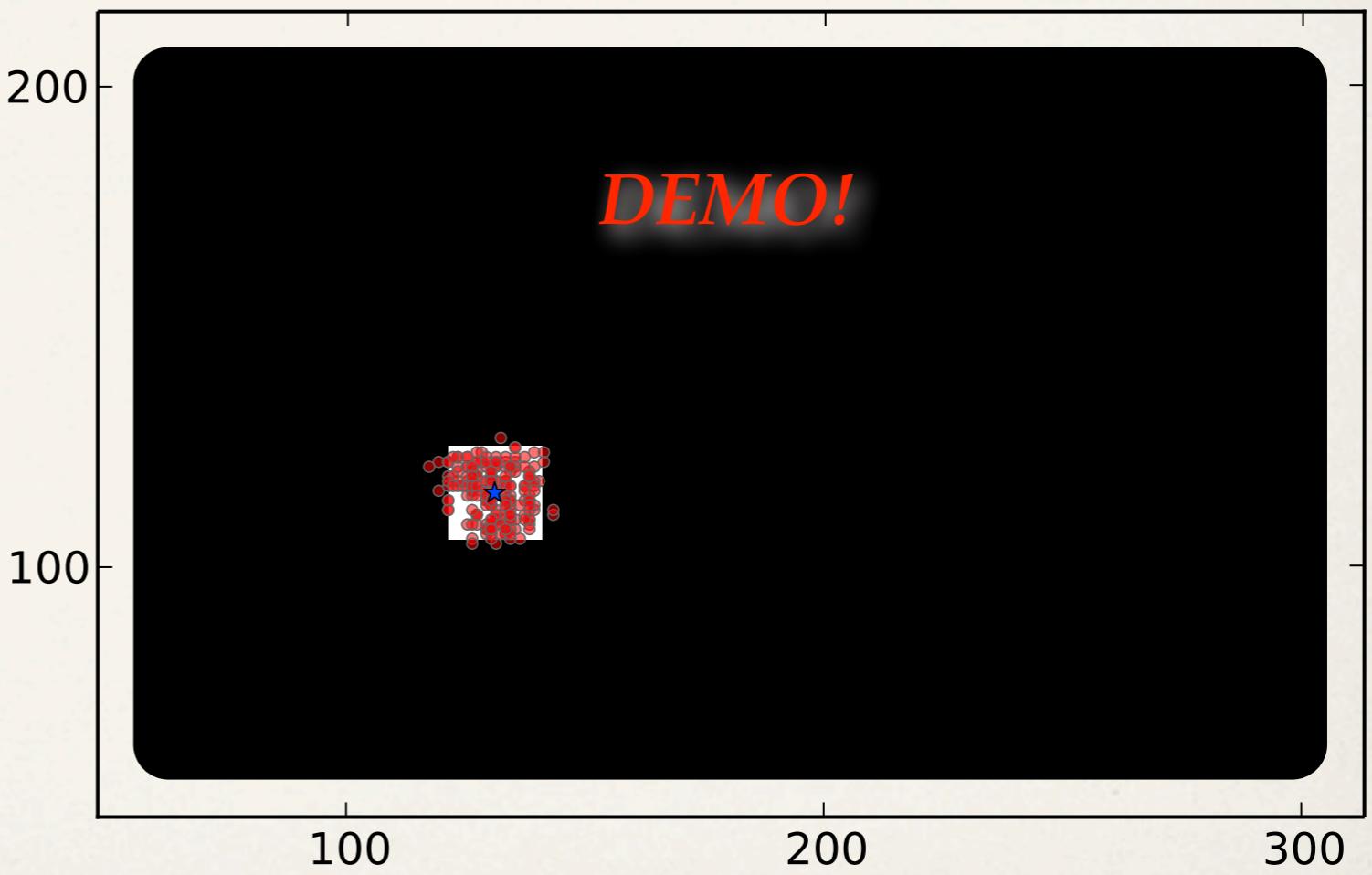
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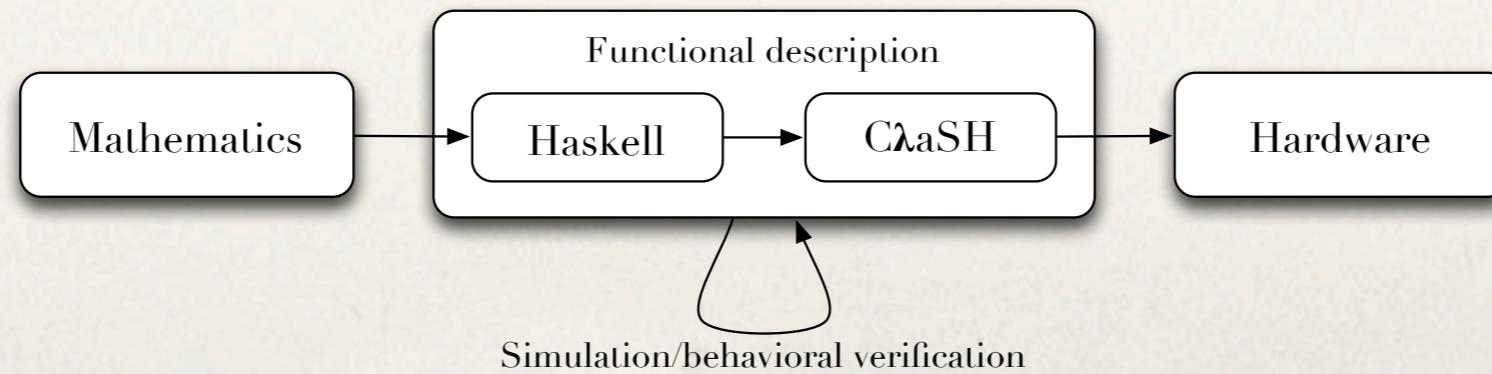


Implementing the particle filter

- ❖ Design method
- ❖ Math to Haskell
- ❖ Haskell to C λ aSH

Design method

- ❖ First step
 - * Reformulate the mathematics of Particle filtering into plain Haskell
- ❖ Second step
 - * Apply small modifications to Haskell code such that it is accepted by the C λ aSH compiler



Math to Haskell

Prediction

- * Apply the state space model to all particles $x_k^{(i)} = f(x_{k-1}^{(i)}, u_k)$
- * All operations are performed independently $f(x_k^{(i)}, u_k) = x_k^{(i)} + u_k$
- * Corresponding higher order function is ***zipWith***

predict $f ps\ us = ps'$

where

$ps' = \text{zipWith } f\ ps\ us$

$$f(x, y, \omega)(\delta_x, \delta_y) = (x', y', \omega)$$

where

$$x' = x + \delta_x$$

$$y' = y + \delta_y$$

Math to Haskell

Normalize

- * Determine sum of weights and apply to all particles
- * Corresponding higher order functions are *foldl* and *zipWith*

$$\tilde{\omega}^{(i)} = \frac{\omega^{(i)}}{\sum_{n=1}^N \omega^{(n)}} \quad \text{for } i = 1 \dots N$$

normalize ps = ps'

where

totω = sum (map weight ps)

ps' = map (λ (x, y, ω) → (x, y, ω / totω)) ps

Haskell to Clash

Prediction

- * Translate lists to Vectors

```
predict :: (Ptl → Ns → Ptl) → [Ptl] → [Ns] → [Ptl]
predict   f           ps      us    = ps'
where
  ps' = zipWith f ps us
```

```
predict :: (Ptl → Ns → Ptl) → (Vector#(D32, Ptl)) → (Vector#(D32, Ns)) → (Vector#(D32, Ptl))
predict   f           ps      us    = ps'
where
  ps' = vzipWith f ps us
```

Haskell to Clash

Prediction

- * Translate lists to Vectors

$predict :: (Ptl \rightarrow Ns \rightarrow Ptl) \rightarrow [Ptl] \rightarrow [Ns] \rightarrow [Ptl]$
 $predict f$

where

$ps' = \boxed{\text{zipWith } f ps us}$

$predict :: (Ptl \rightarrow Ns \rightarrow Ptl) \rightarrow (\text{Vector } D32 \text{ } Ptl) \rightarrow (\text{Vector } D32 \text{ } Ns) \rightarrow (\text{Vector } D32 \text{ } Ptl)$
 $predict f$

where

$ps' = \boxed{vzipWith } f ps us$

Haskell to CλaSH

Normalize

- * Translate lists to Vectors
- * Use fixed point representation for weights

```
normalize :: [Ptl] → [Ptl]
normalize ps = ps'
where
  totω = sum (map weight ps)
  ps   = map (λ (x, y, ω) → (x, y, ω / totω)) ps
```

```
normalize :: (Vector D32 Ptl) → (Vector D32 Ptl)
normalize ps = ps'
where
  totω      = sum (vmap weight ps)
  totωrecip = fprecip totω
  ps        = vmap (λ (x, y, ω) → (x, y, ω * totωrecip)) ps
```

Haskell to CλaSH

Normalize

- * Translate lists to Vectors
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Haskell to Clash

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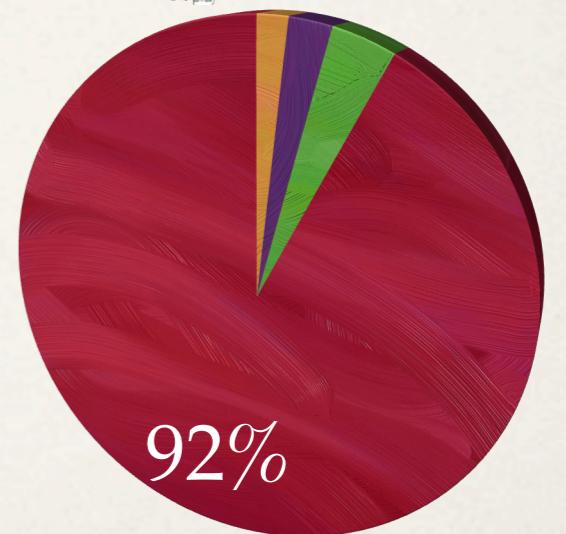
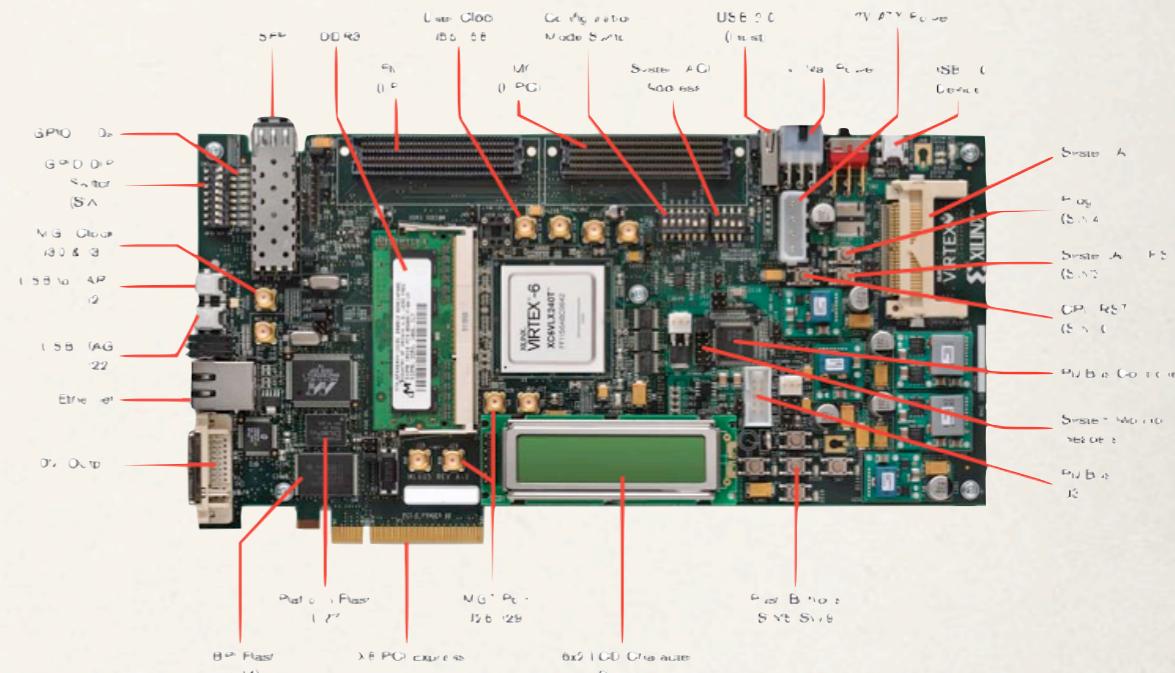
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```

Results

- ❖ Parallel particle filter with 32 particles synthesized for FPGA
 - ❖ Area = about 40k LUTs
 - ❖ PF can be synthesized but is slow
 - ❖ Resampling step is bottleneck in both area and clockfrequency
- ❖ For larges PFs, we need a trade off between area and execution time



Conclusions

- A completely parallel Particle Filter has been implemented
- Higher order functions are a natural way to reason about structure in both the mathematical formulation and hardware
- Haskell code needs only small modifications before it is accepted by the C λ aSH compiler
- Fully parallel resampling is a bottleneck in both area and clock frequency

Future Work

- ❖ Extend particle filter to more particles and more complex tracking
- ❖ Develop area vs time time trade off based on functional description

Questions ?
