Unfreezing the Robot: Navigation in Dense Human Crowds

Pete Trautman, Andreas Krause, Jeremy Ma and
Richard M. Murray

Why is Autonomous Crowd Navigation Needed?

- Malls, hospitals, ...

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- Cafeterias!

Pioneer 3-DX

The Freezing Robot Problem

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Independent agents $\implies$ uncertainty explosion

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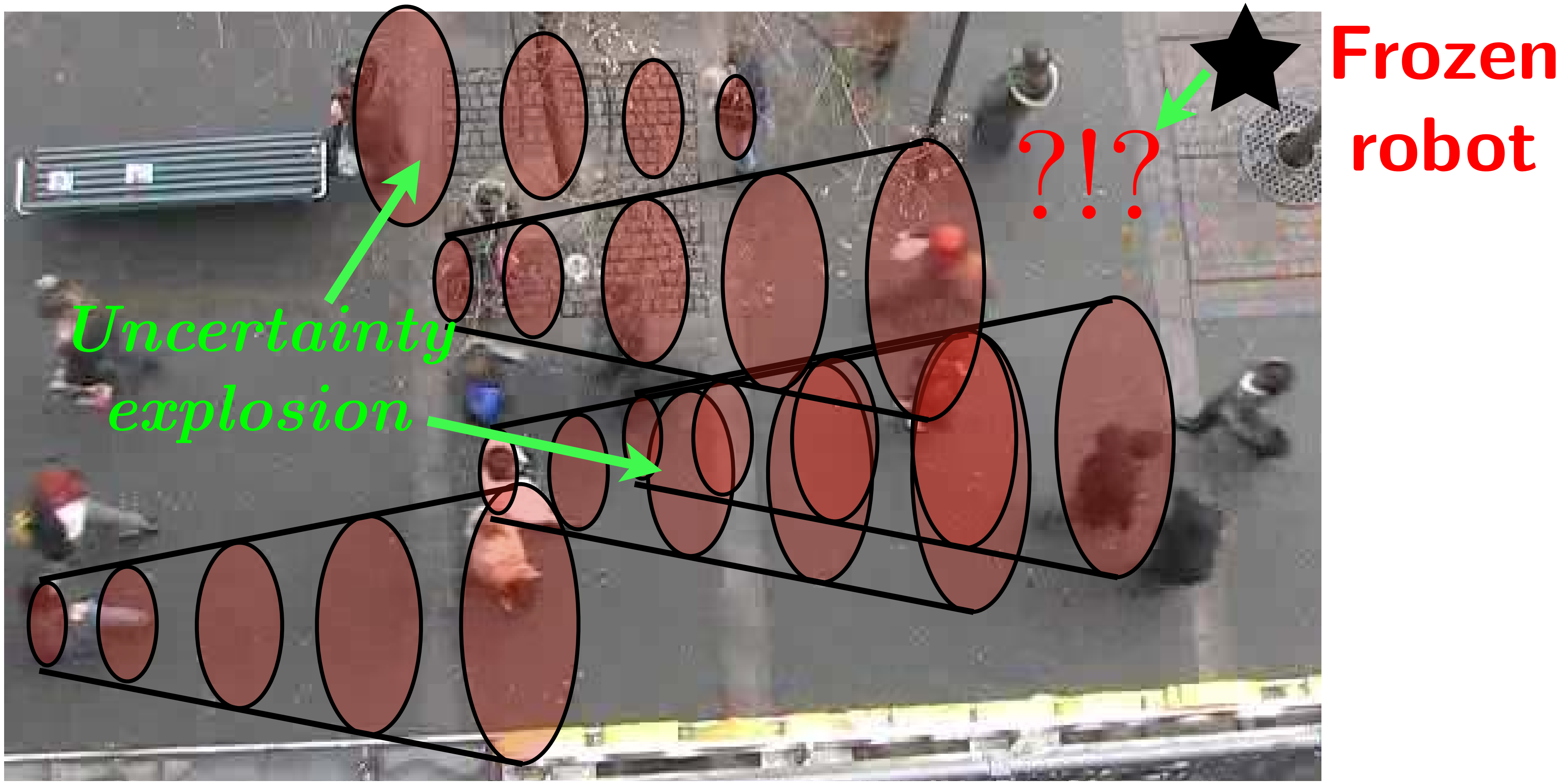
Independent agents $\Longrightarrow$ uncertainty explosion



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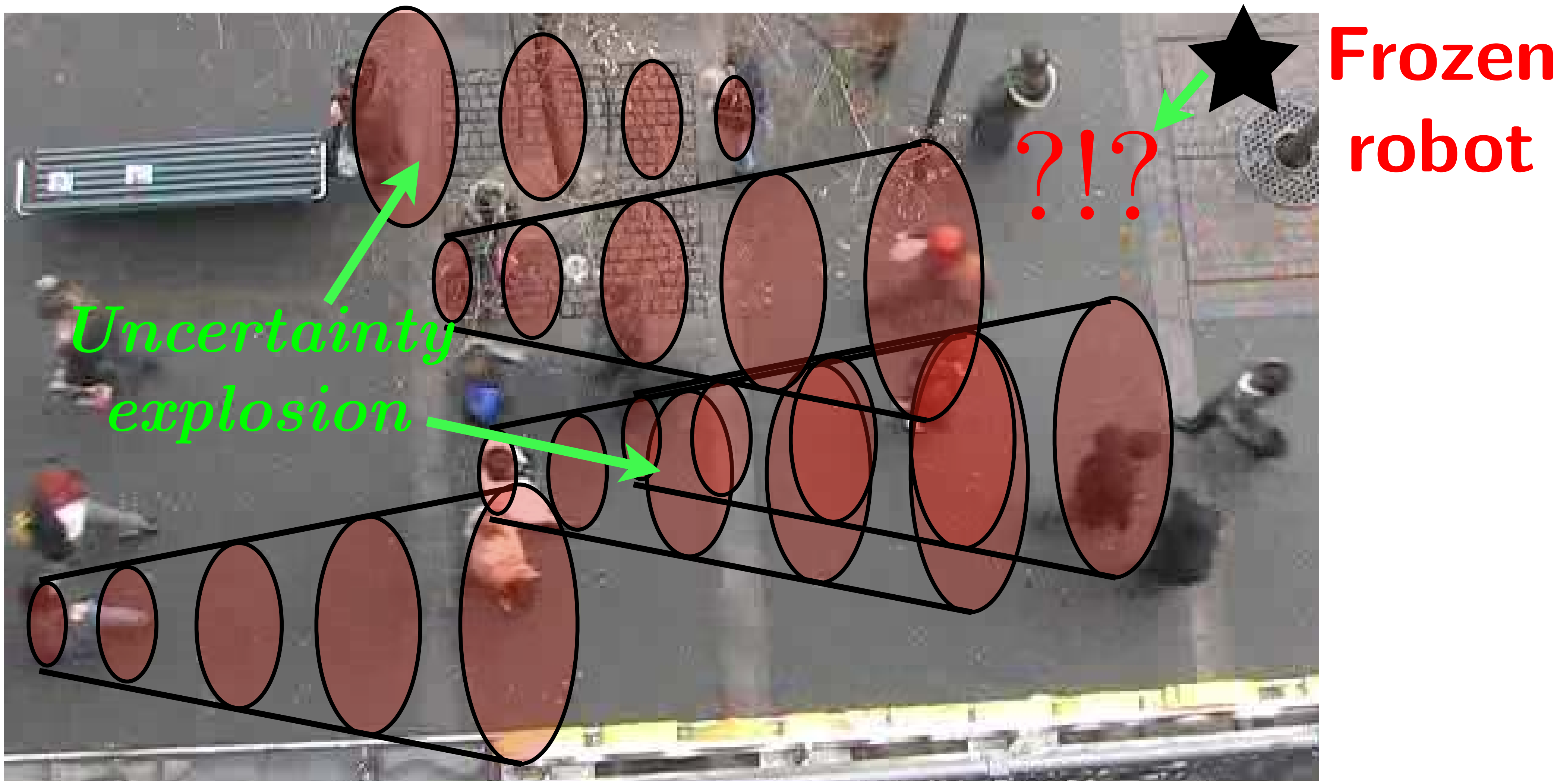
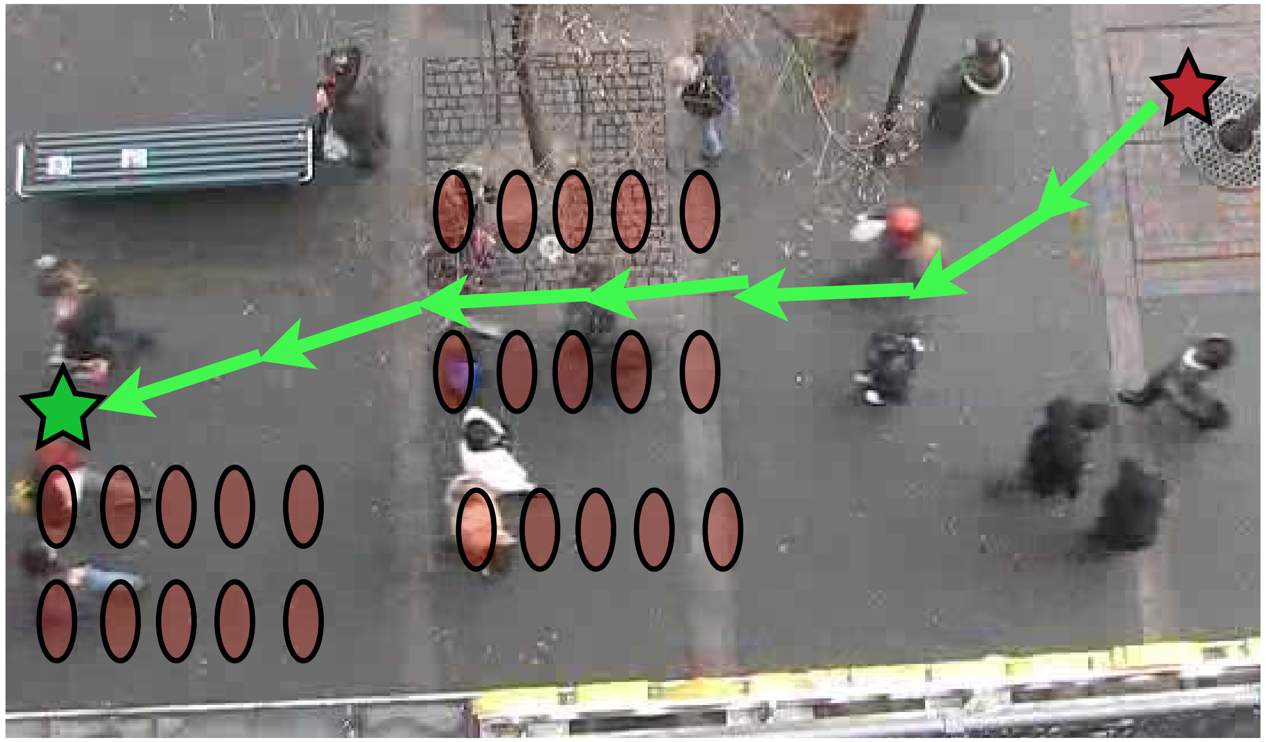


Uncertainty explosion $\implies$ **freezing robot problem**

Approaches to Solving the Freezing Robot Problem



- State of the art methods assume culprit of FRP is uncertainty explosion [6]

- Control covariance, keep cost low (call it "constant covariance" method)

- Precise agent dynamic modeling has same motivation [18,16,2,7,9]

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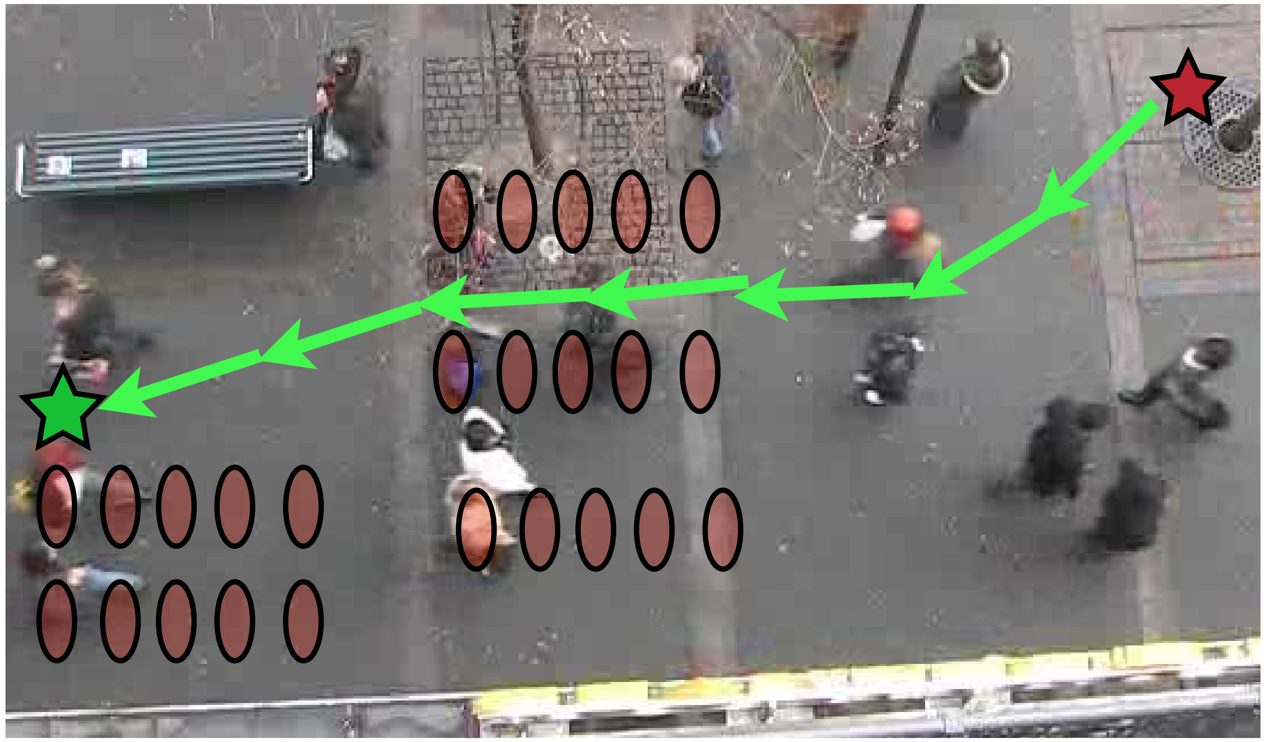

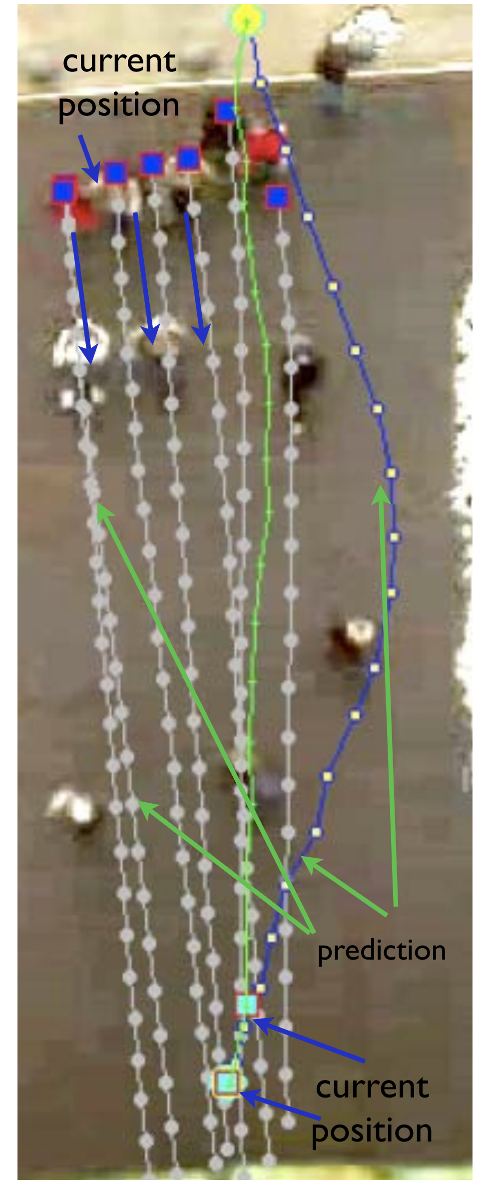

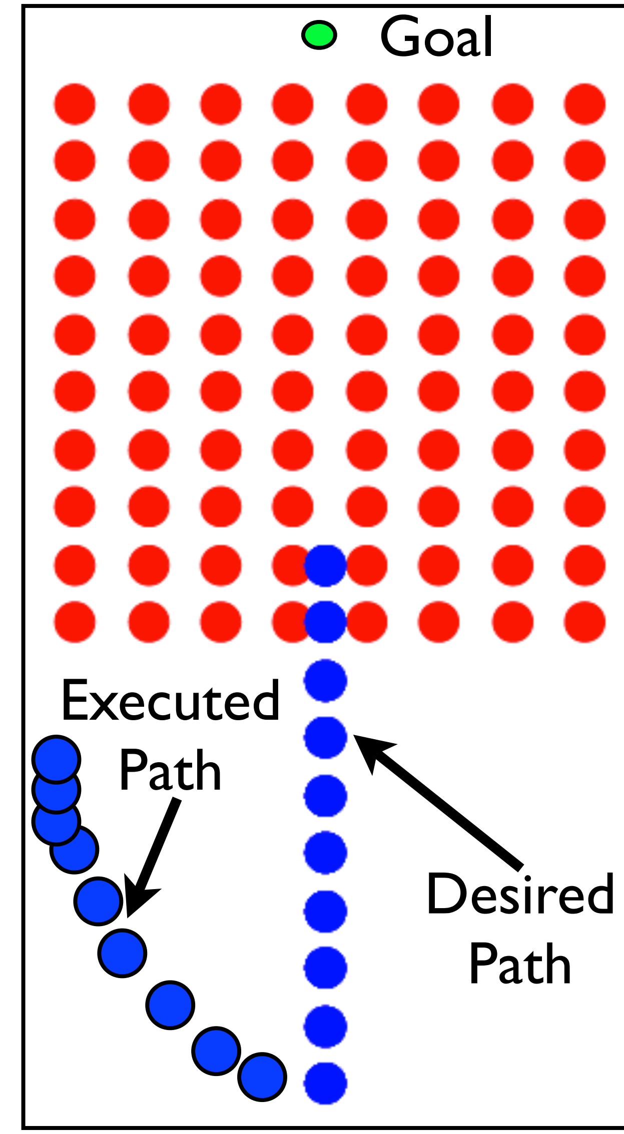

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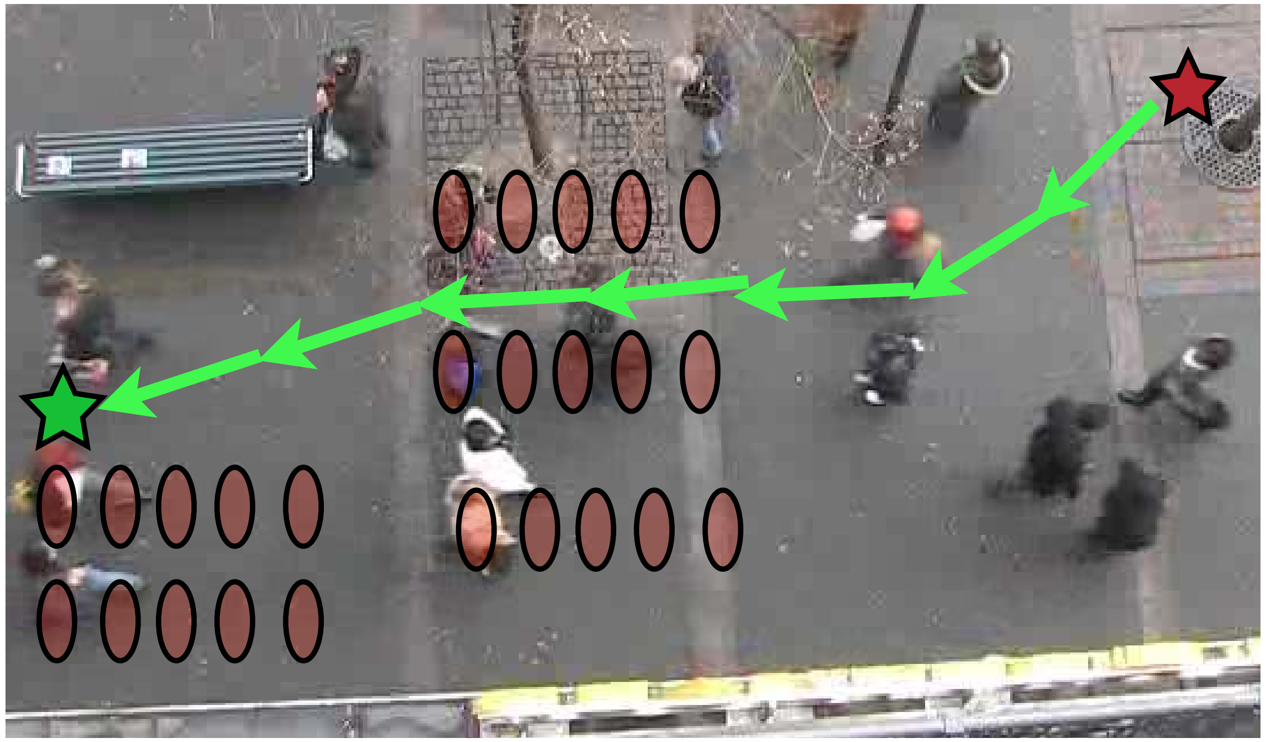

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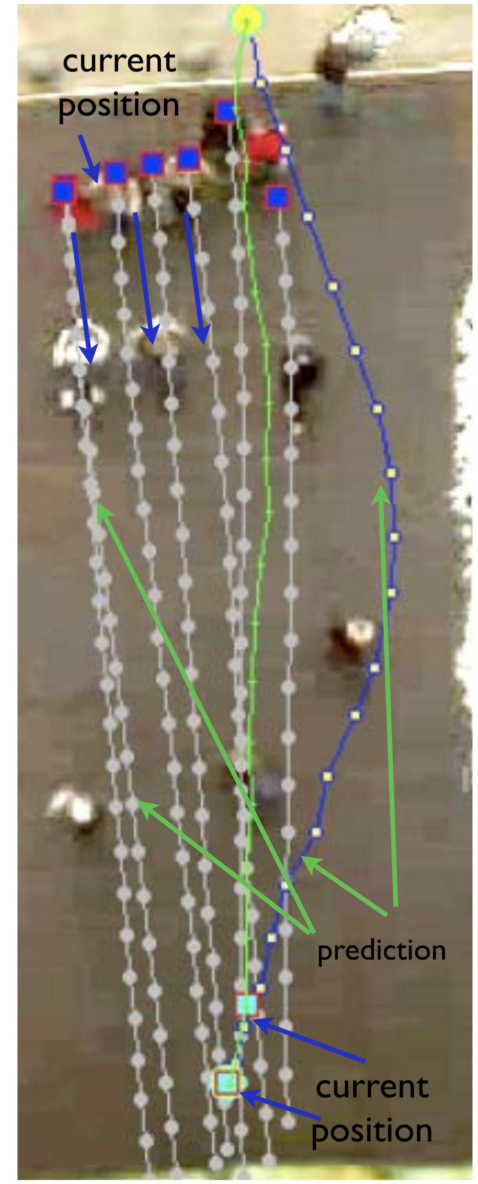
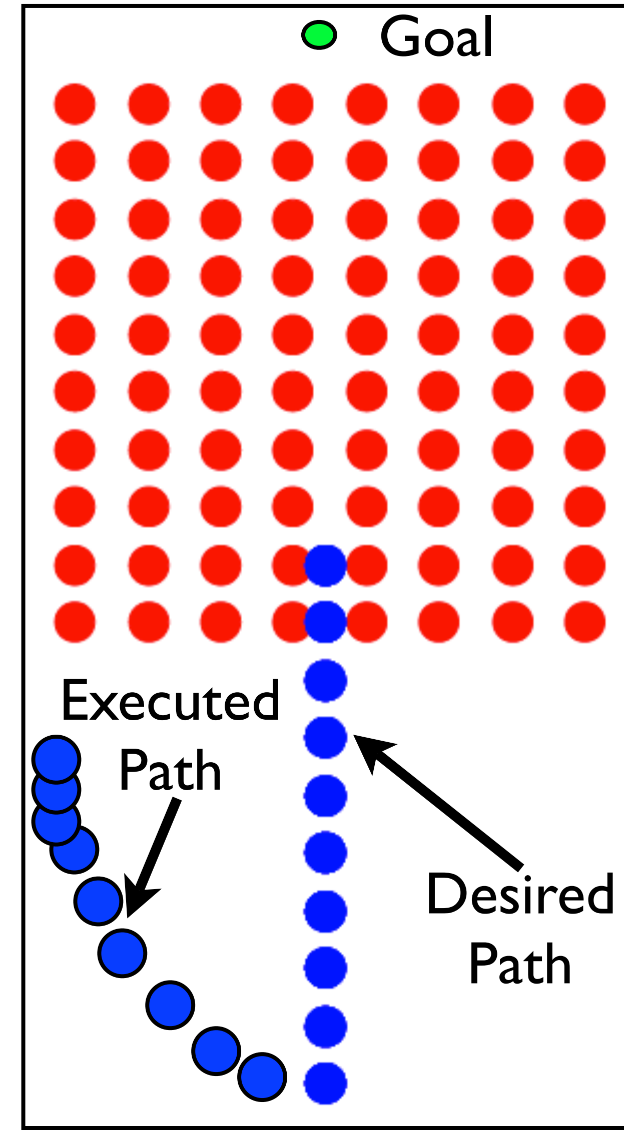


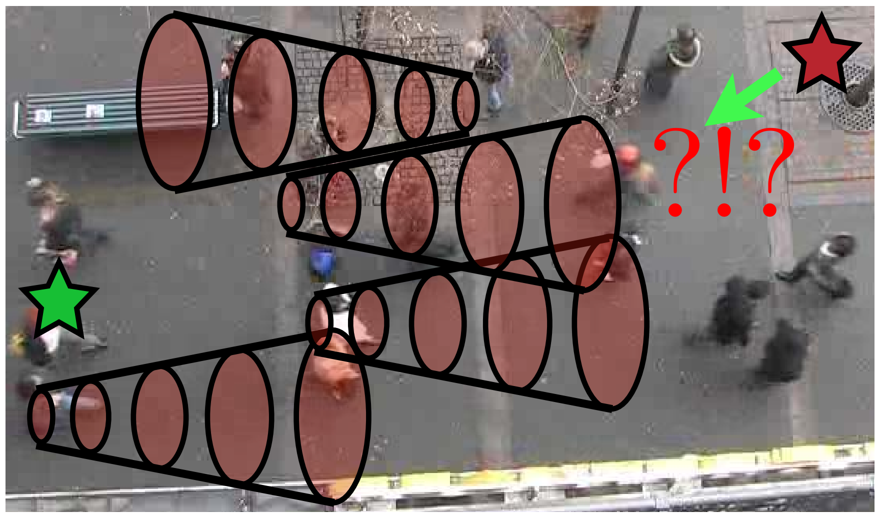


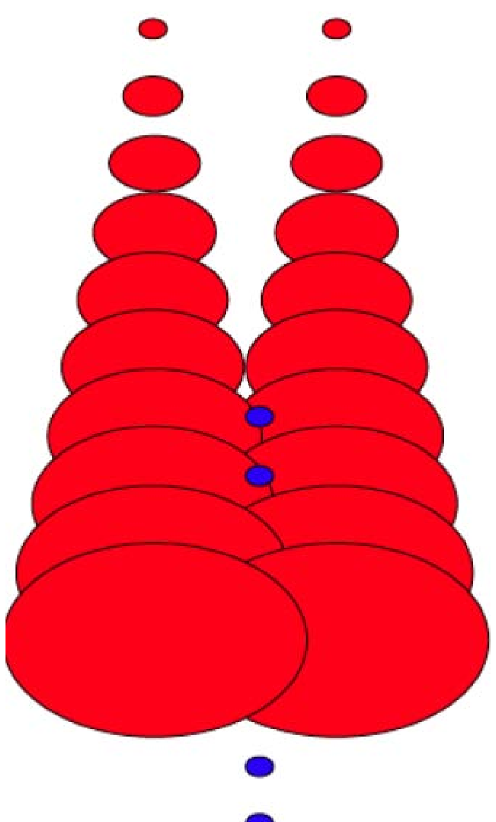
BUT: Severely crowded environments: all paths lower bounded by large cost

Conclusion: *improving prediction* or *reducing covariance* cannot be expected to solve the freezing robot problem

Approaches Continued

"Agnostic" robot:
agent independence





- Const. cov. unreliable
- Reactive planning unreliable

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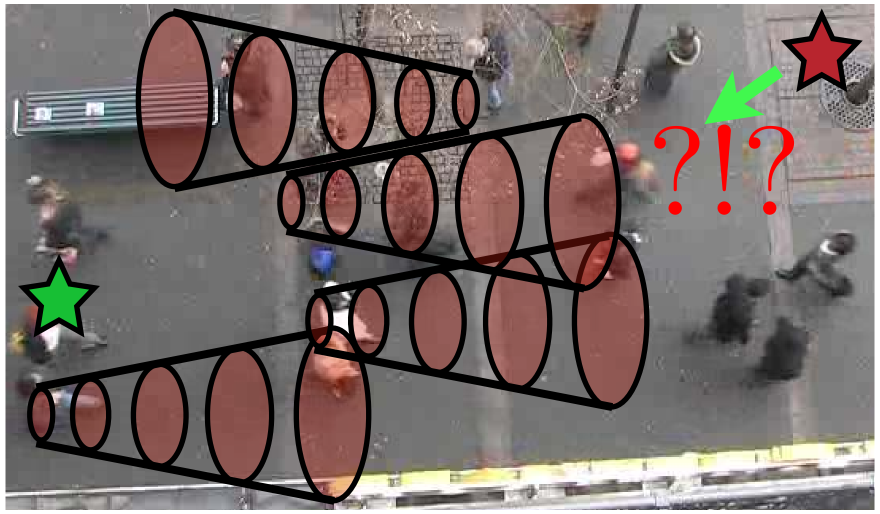
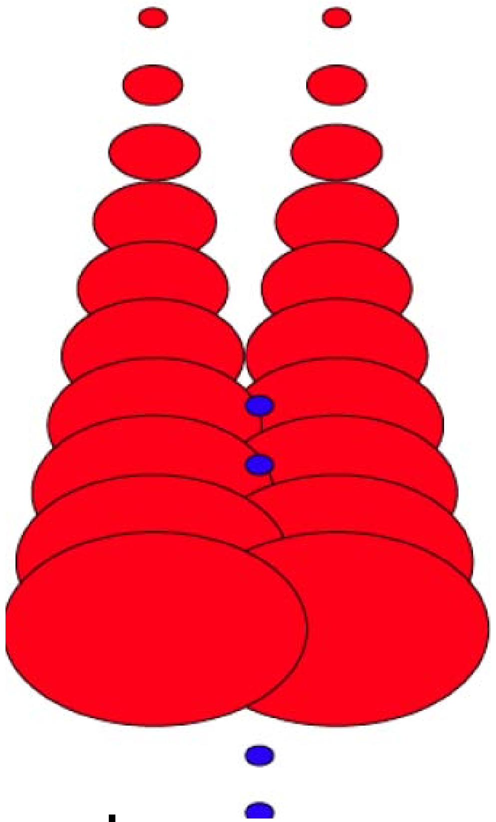




"Cooperative" robot: robot/agent system

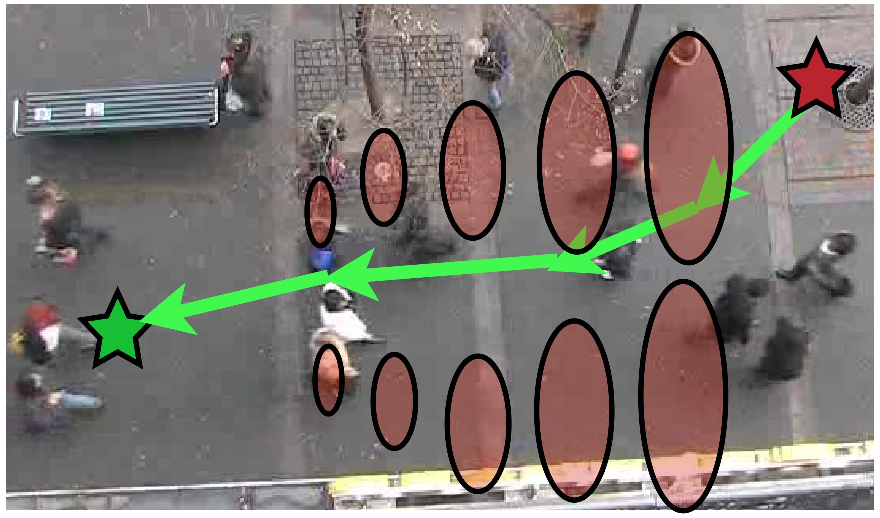
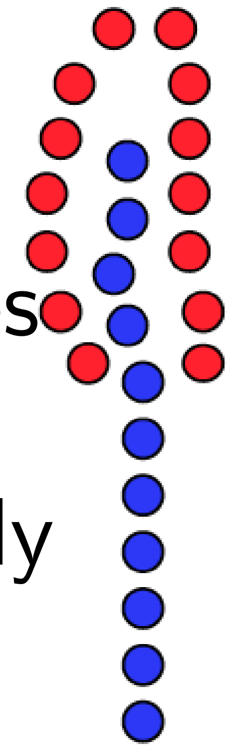


Illustration: robot cooperates with agents to proceed optimally



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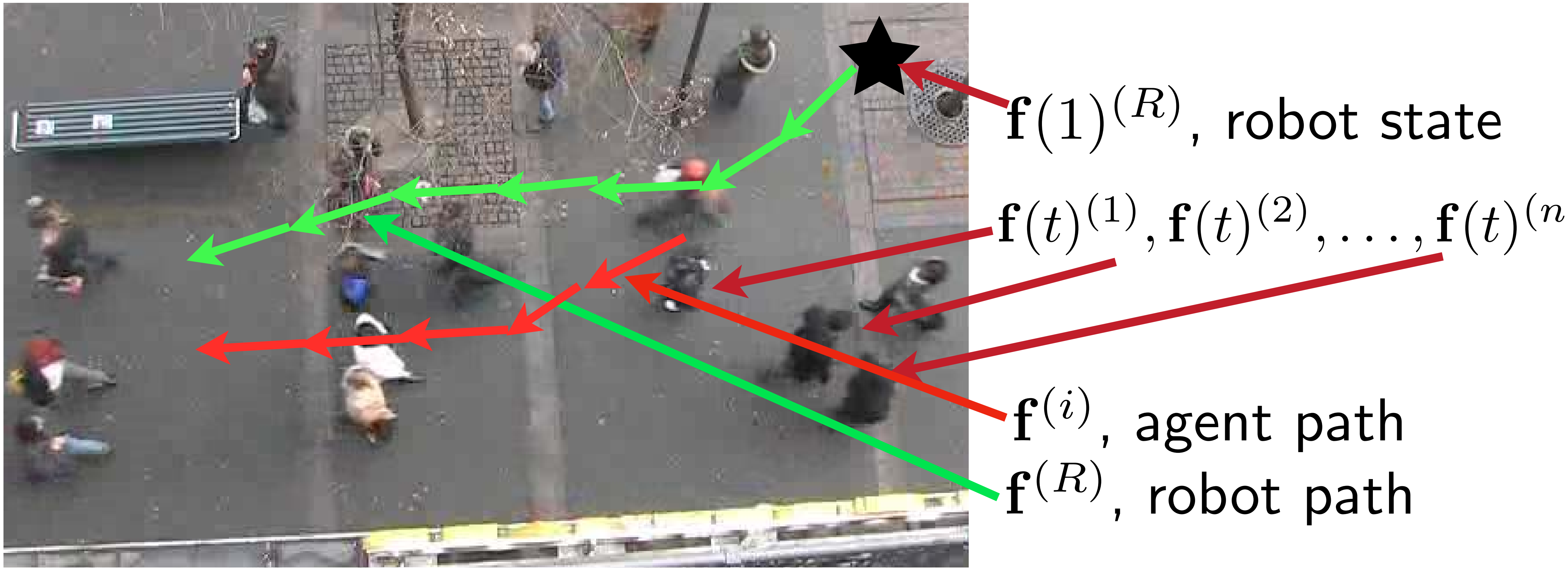
Our Solution



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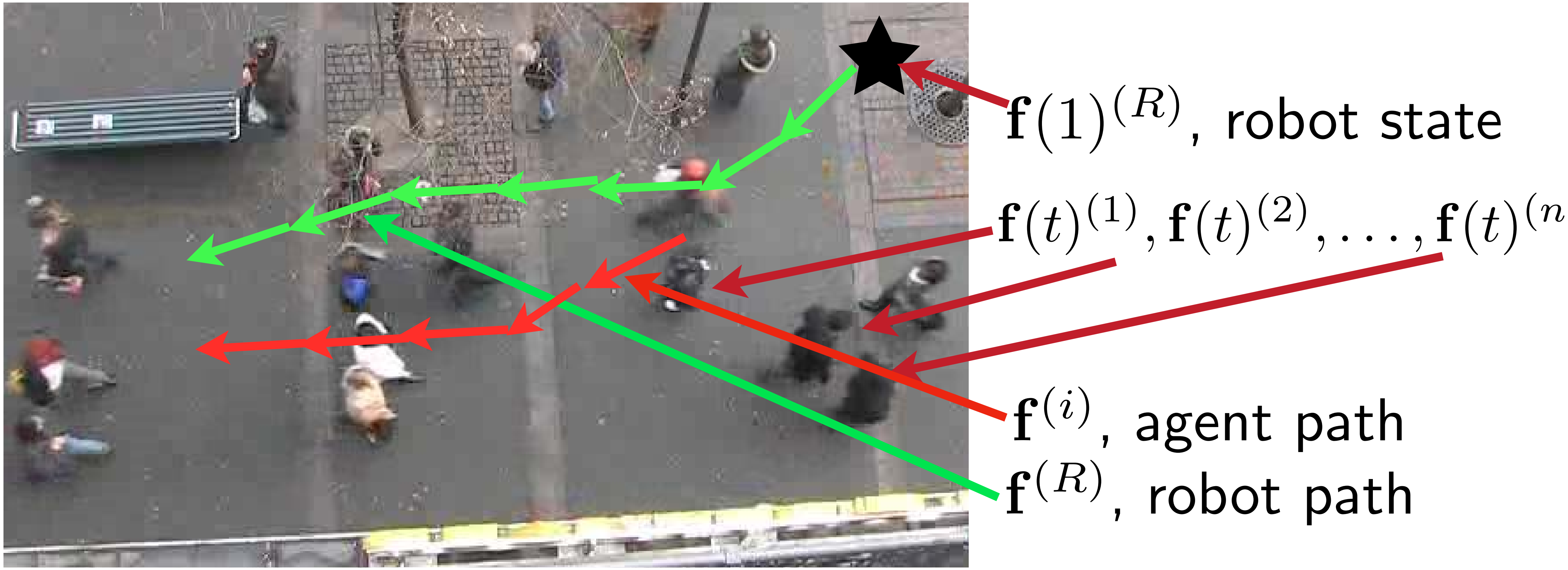

— $\mathbf{f}^{(i)}$ is agent i's *continuous path* in the plane $\mathbb{R}^2$:

$$\mathbf{f}^i \colon [0, \infty] \rightarrow \mathbb{R}^2$$
$$: t \mapsto [x(t)^{(i)}, y(t)^{(i)}]$$

— $\mathbf{f}(t) = (\mathbf{f}(t)^{(1)}, \mathbf{f}(t)^{(2)}, \ldots, \mathbf{f}(t)^{(n)})$ is concatenation of n agent paths

Challenge: how to efficiently and accurately model random, continuous trajectories (functions)

Gaussian Processes for Trajectory Modeling

GP prior: distribution
over functions
$\Longrightarrow$ models trajectories well

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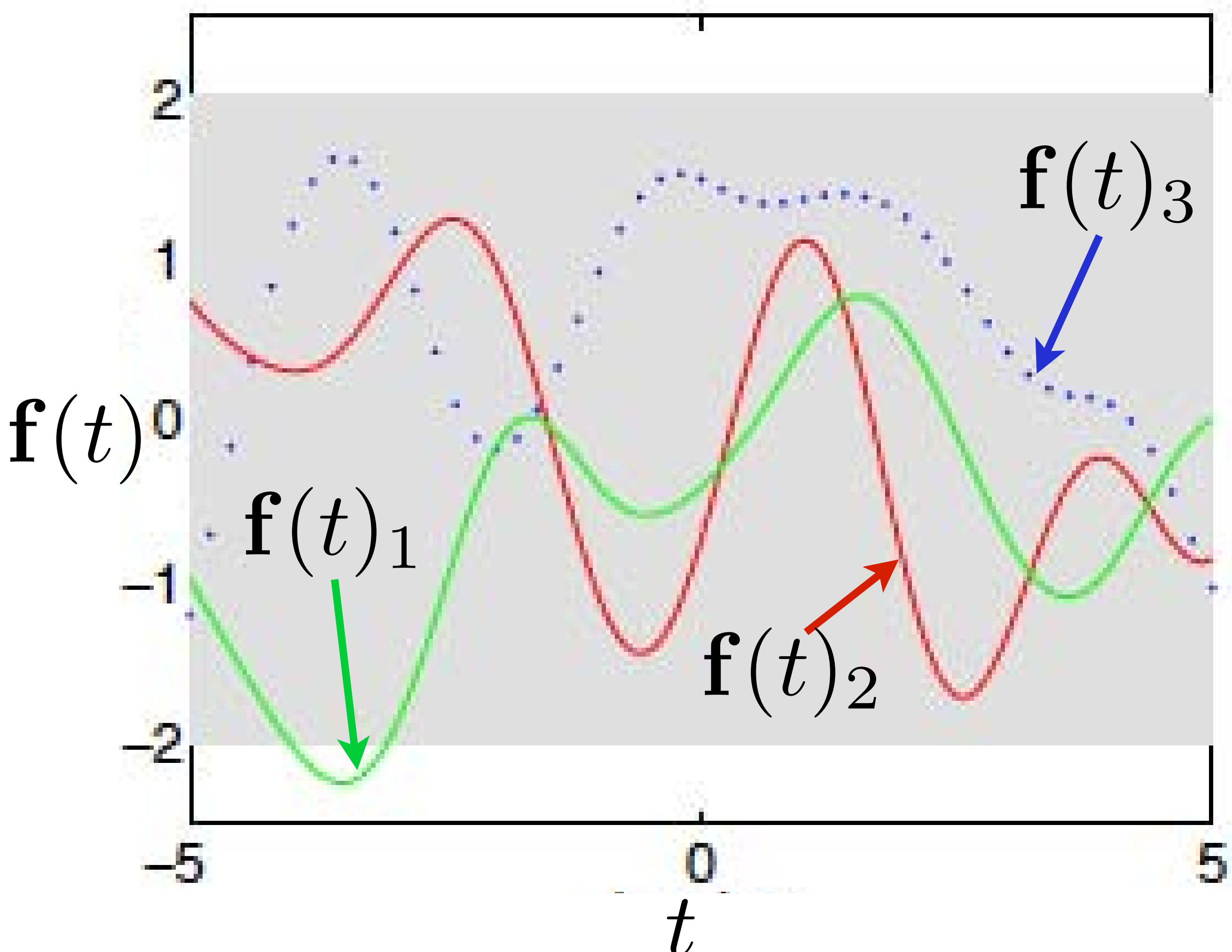

- Draw *trajectories*

  $\mathbf{f}(t)_i \sim GP(0, k)$

- kernel function k controls smoothness of $x(t)$

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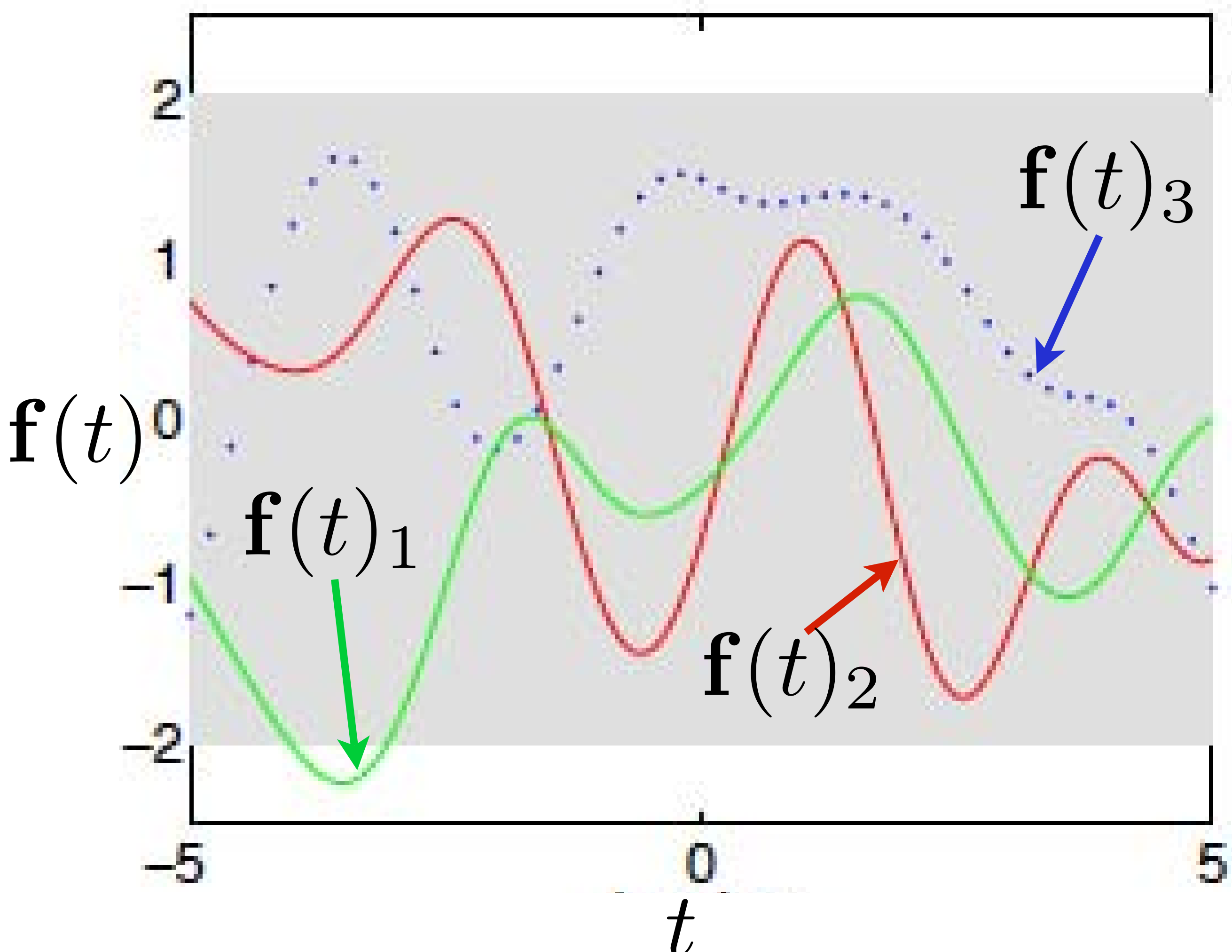
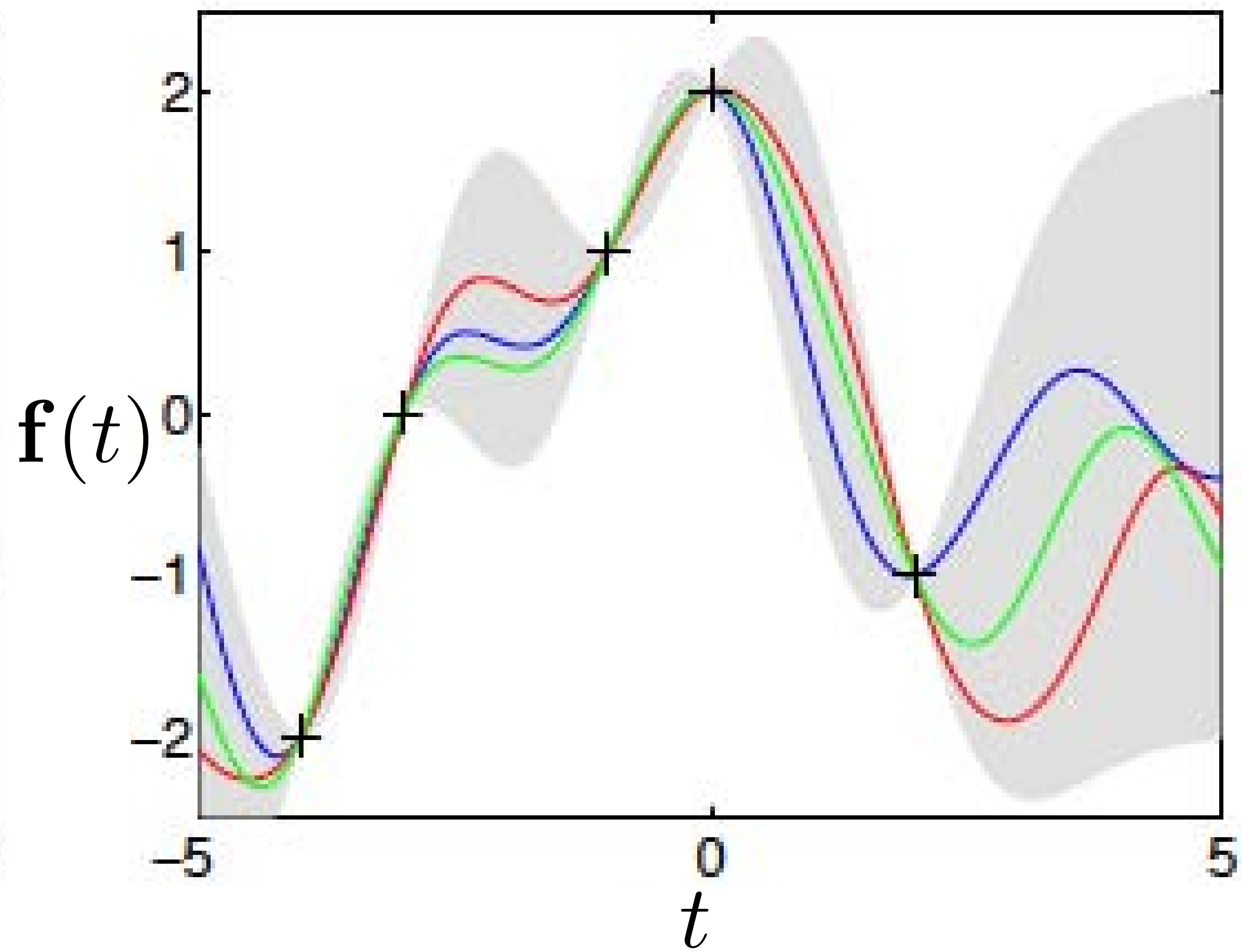


GP posterior: incorporates information at any point along trajectory



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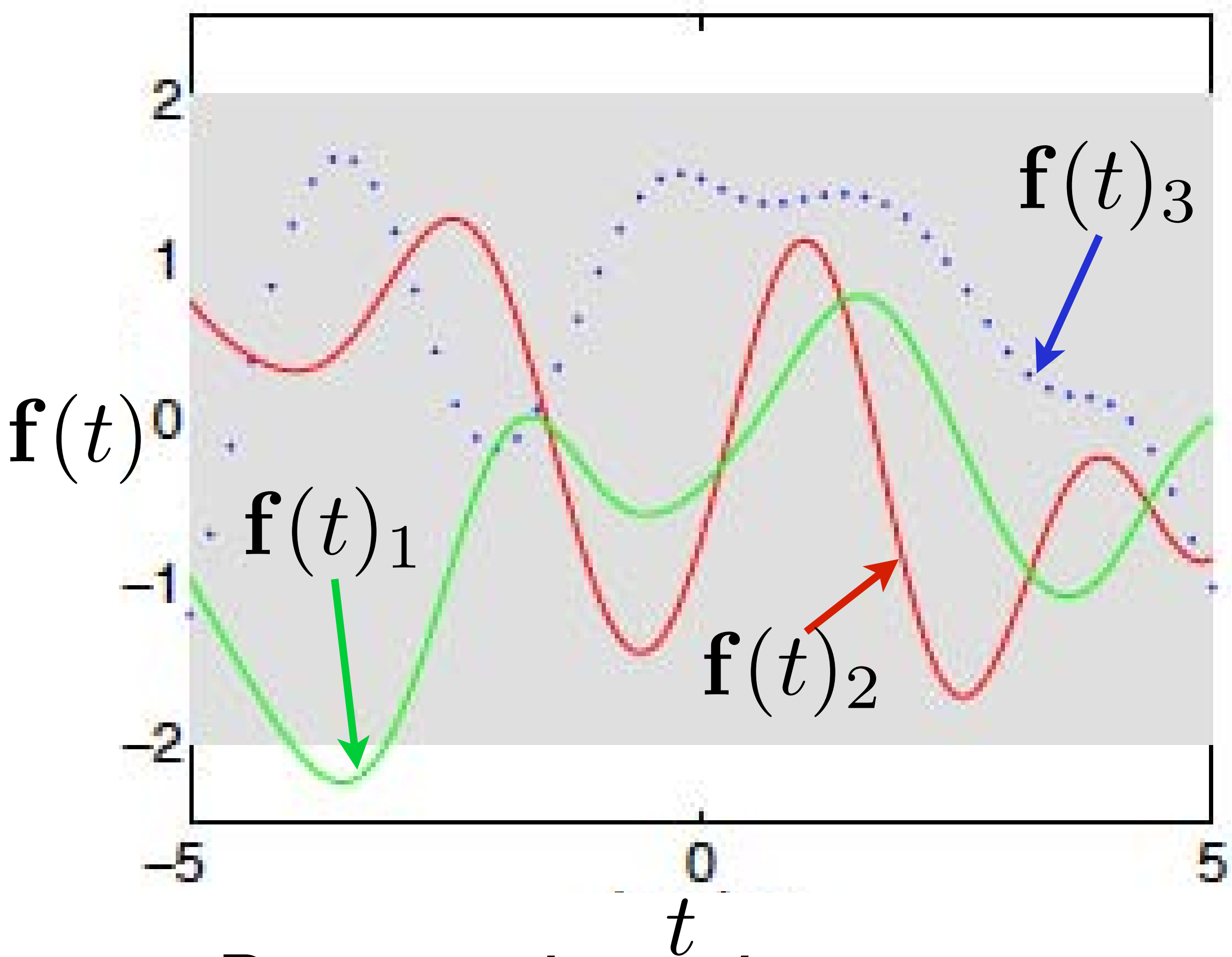

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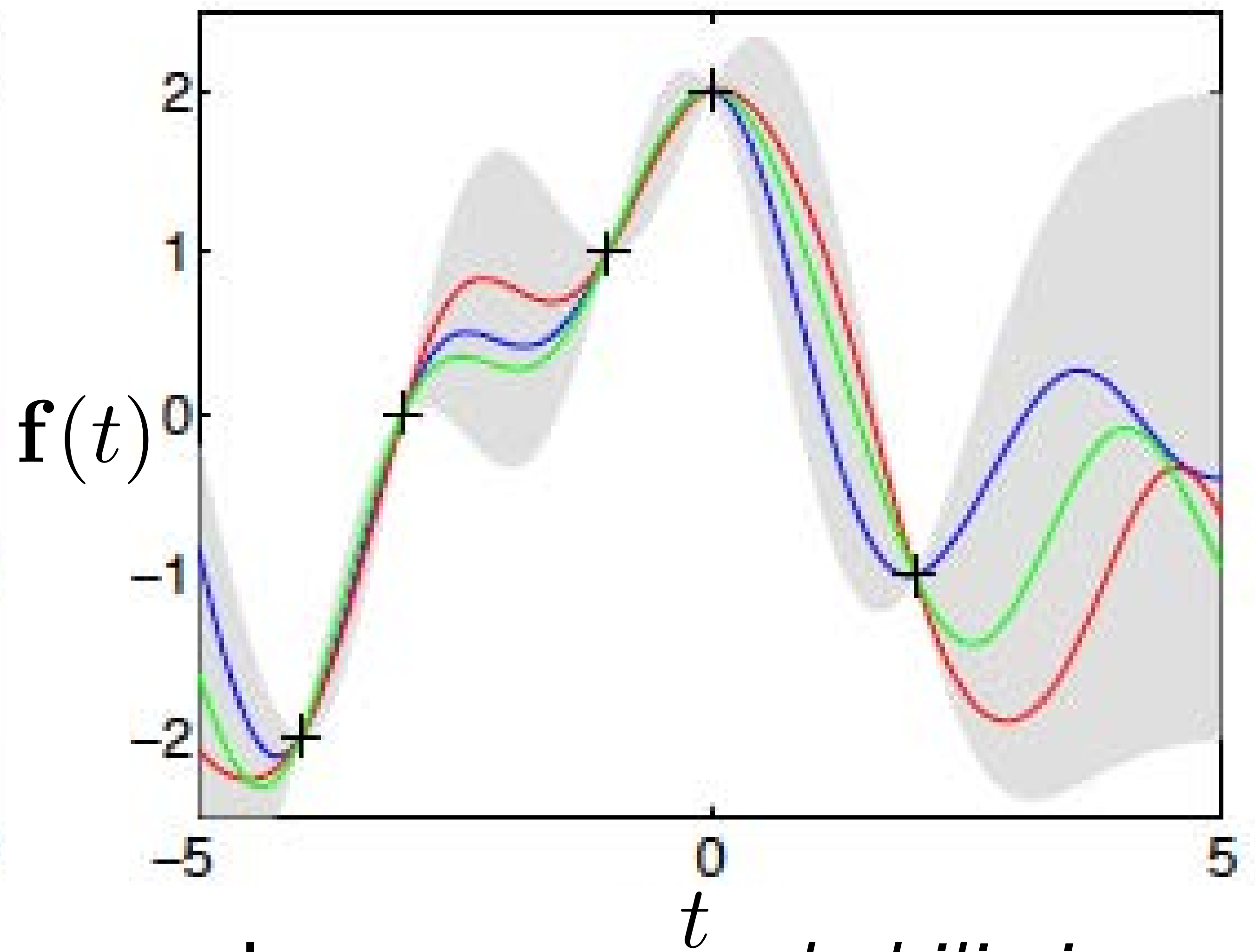
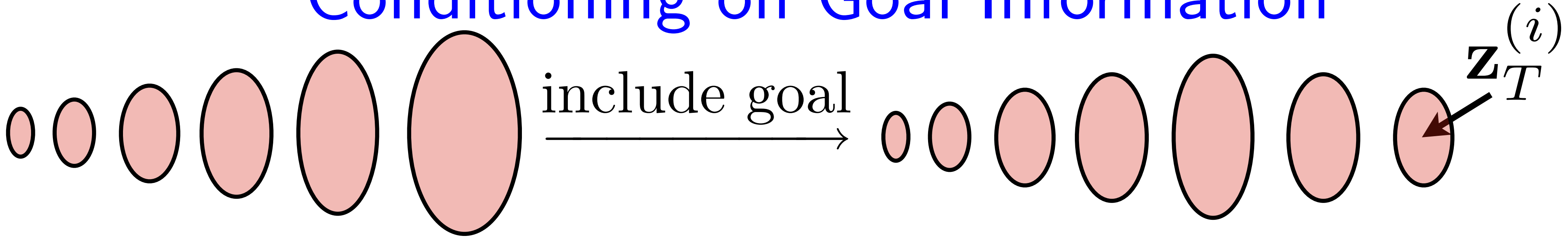


- Incorporate *probabilistic* goal information
- Encode smoothness in a non-Markovian way

Conditioning on Goal Information



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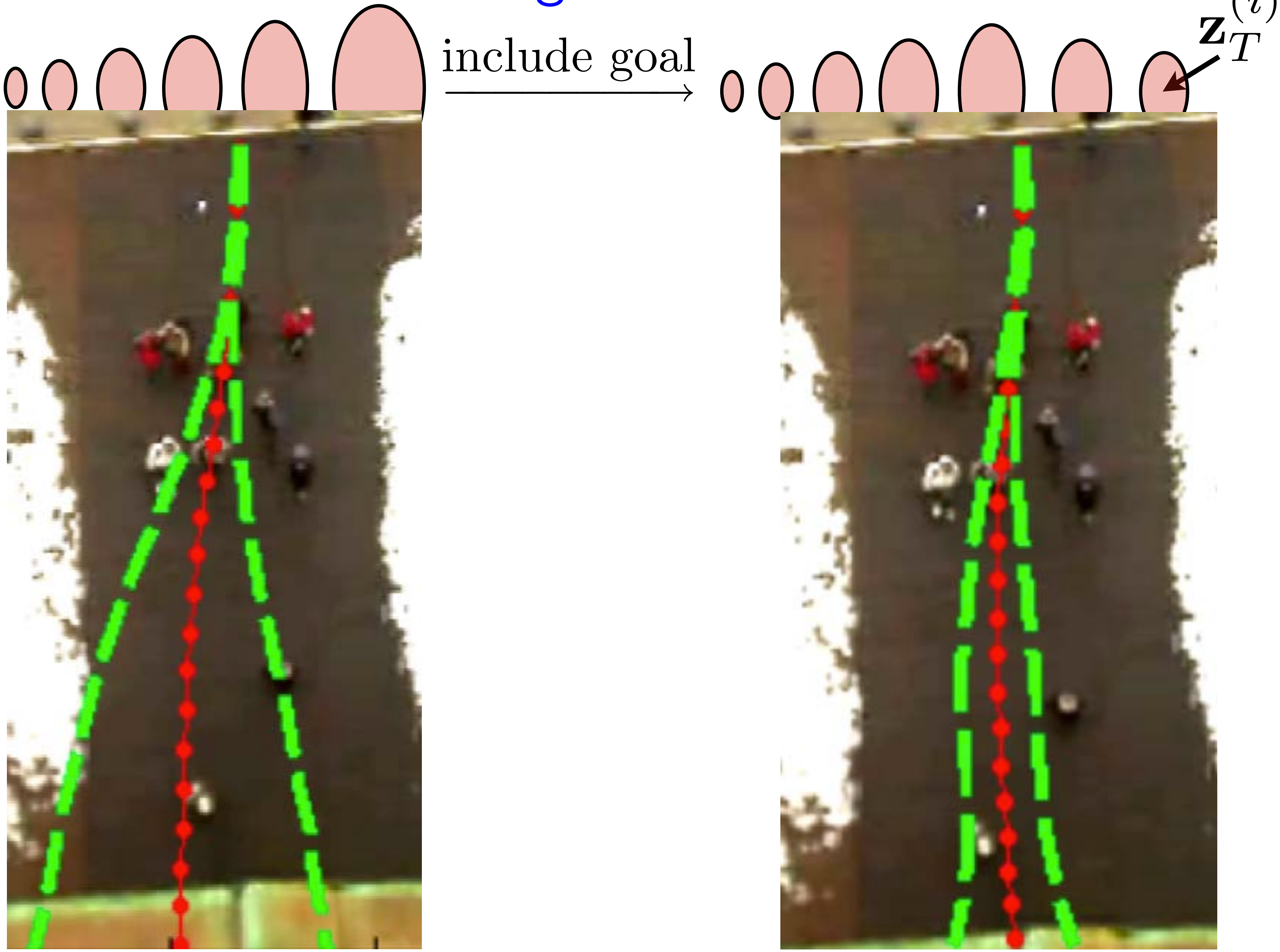

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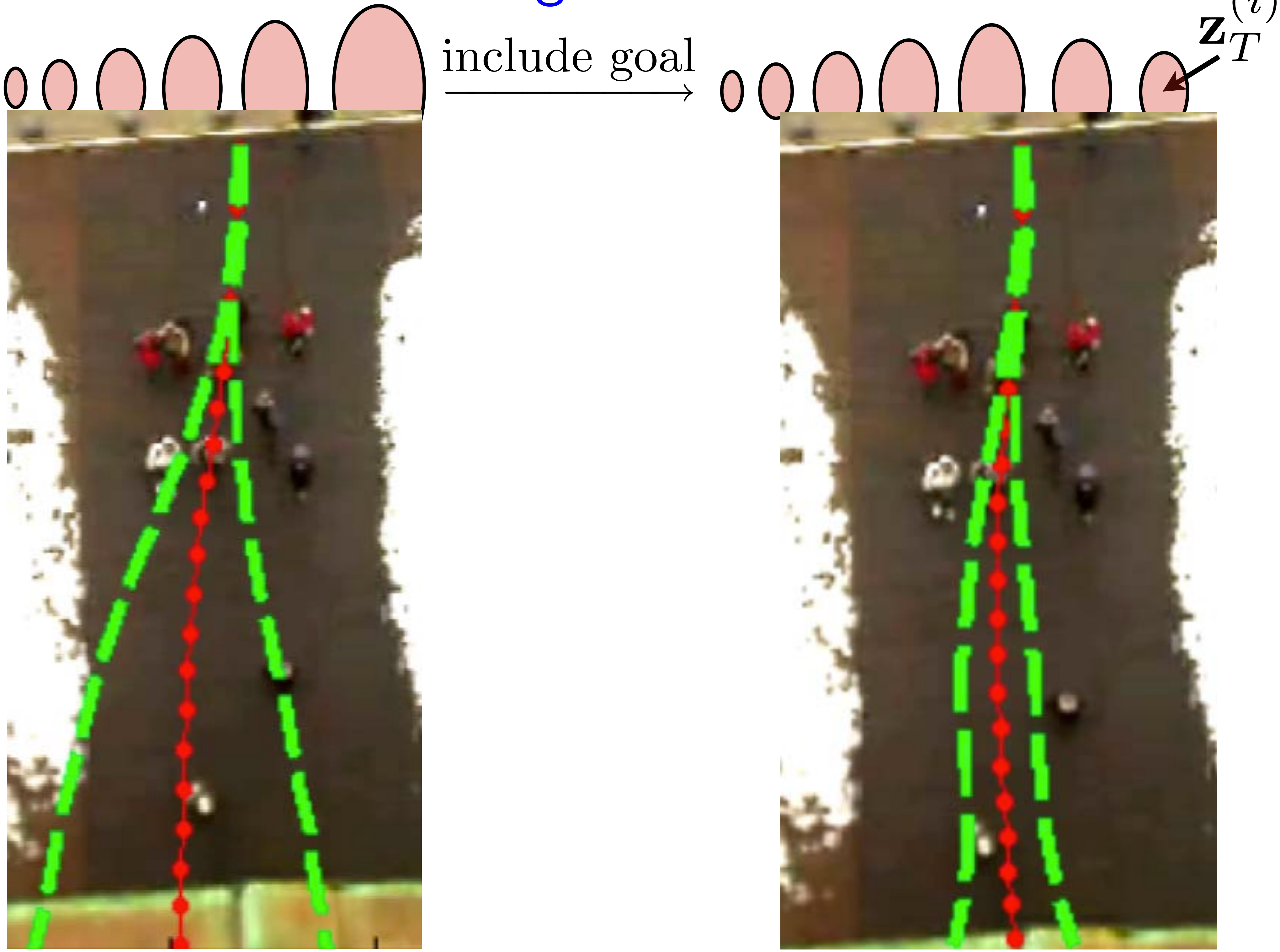
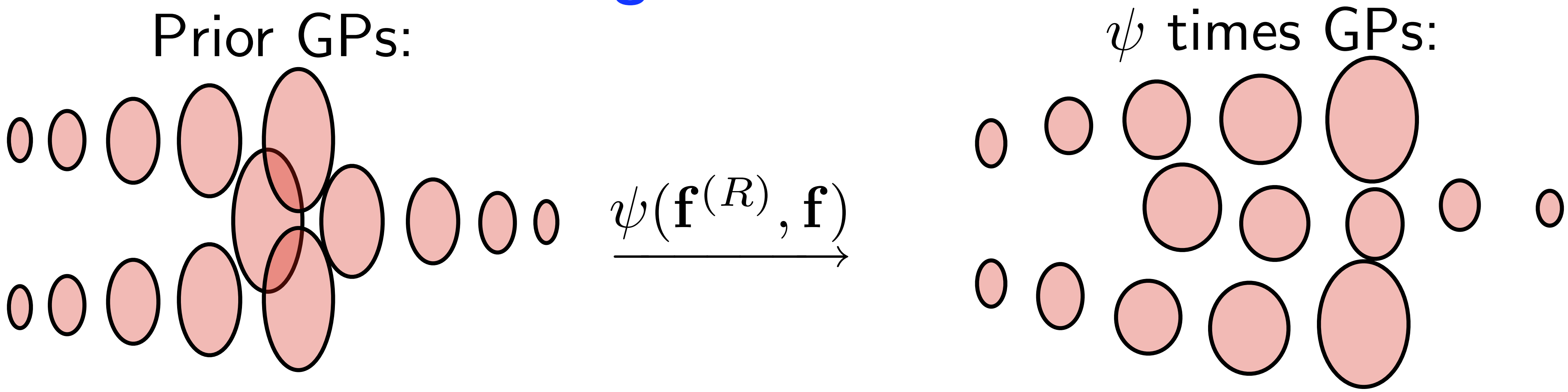


Train prior GPs to find $k^{(i)}$, condition on goal information $\mathbf{z}_T^{(i)}$:

$$p_{k^{(R)}}(\mathbf{f}^{(R)} \mid \mathbf{z}_{1:t}, \mathbf{z}_T^{(R)}), p_{k^{(1)}}(\mathbf{f}^{(1)} \mid \mathbf{z}_{1:t}^{(1)}, \mathbf{z}_T^{(1)}), \ldots, p_{k^{(n)}}(\mathbf{f}^{(n)} \mid \mathbf{z}_{1:t}, \mathbf{z}_T^{(n)})$$

Interacting Gaussian Processes



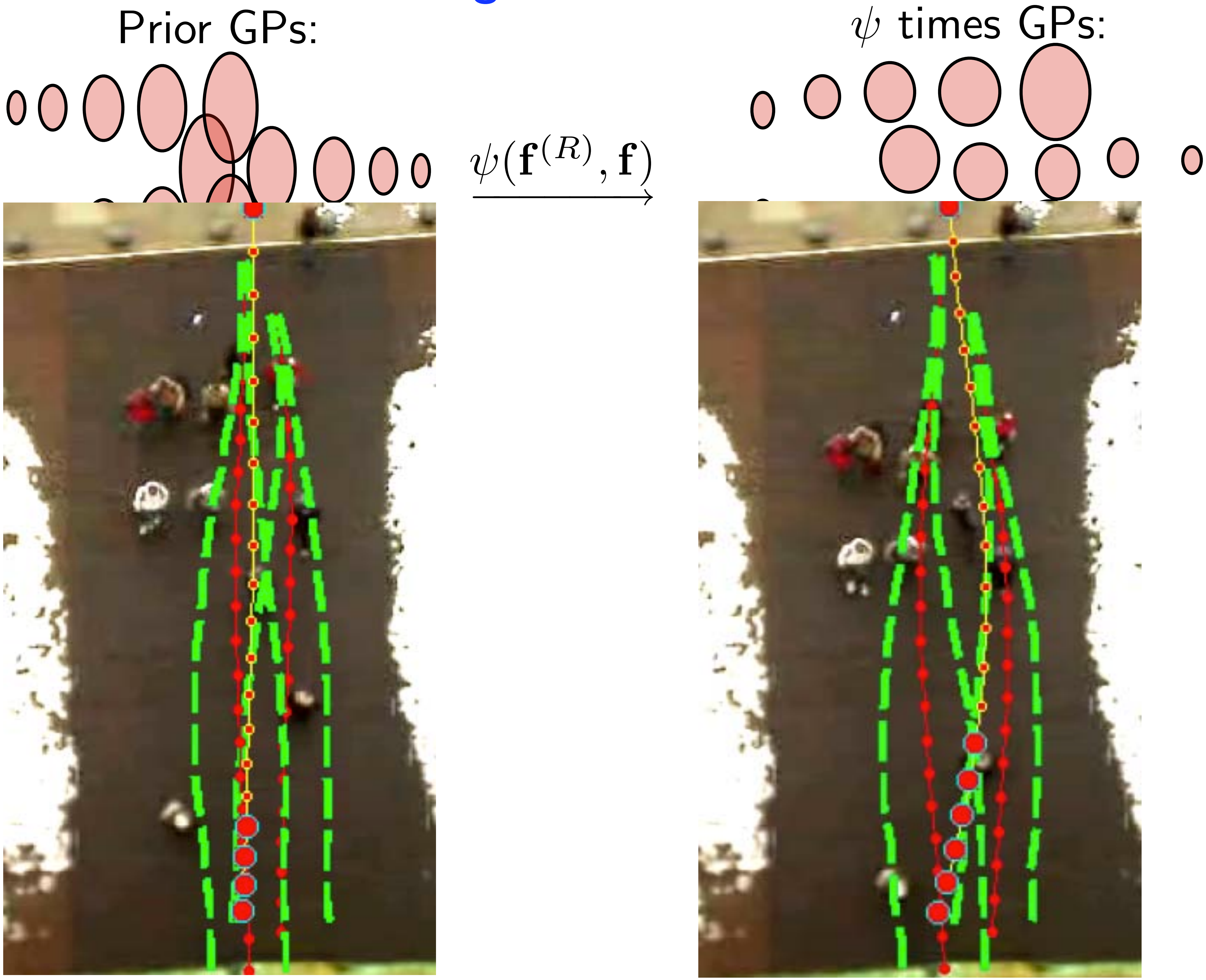
Interacting Gaussian Processes

Prior GPs:

$$\xrightarrow{\psi(\mathbf{f}^{(R)}, \mathbf{f})}$$

ψ times GPs:

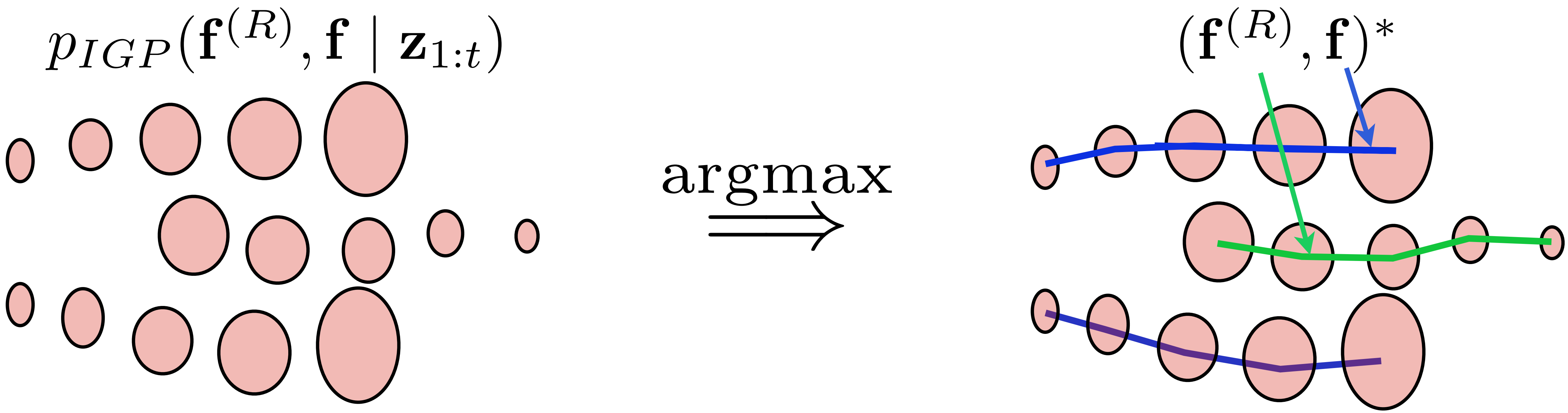
Interacting Gaussian Processes



$$p(\mathbf{f}^{(R)}, \mathbf{f} \mid \mathbf{z}_{1:t}) = \frac{1}{Z}\psi(\mathbf{f}^{(R)}, \mathbf{f}) \prod_{i=R}^{n} p_{k^{(i)}}(\mathbf{f}^{(i)} \mid \mathbf{z}_{1:t}, \mathbf{z}_T^{(i)})$$

Navigation with Interacting Gaussian Processes

$p(\mathbf{f}^{(R)}, \mathbf{f} \mid \mathbf{z}_{1:t})$ suggests a natural way to perform navigation: at time t, find that MAP of the posterior



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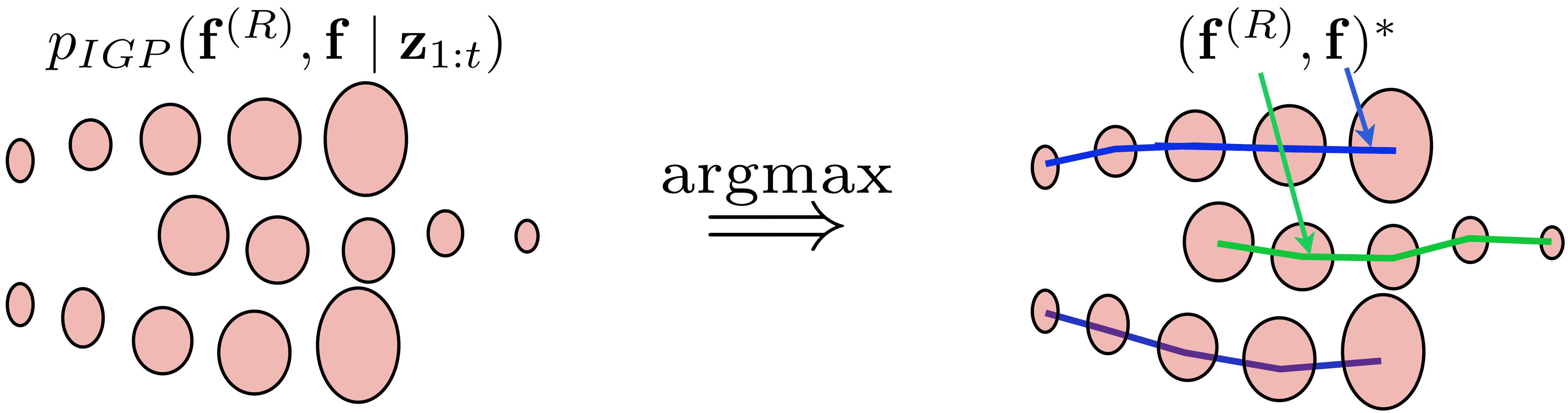
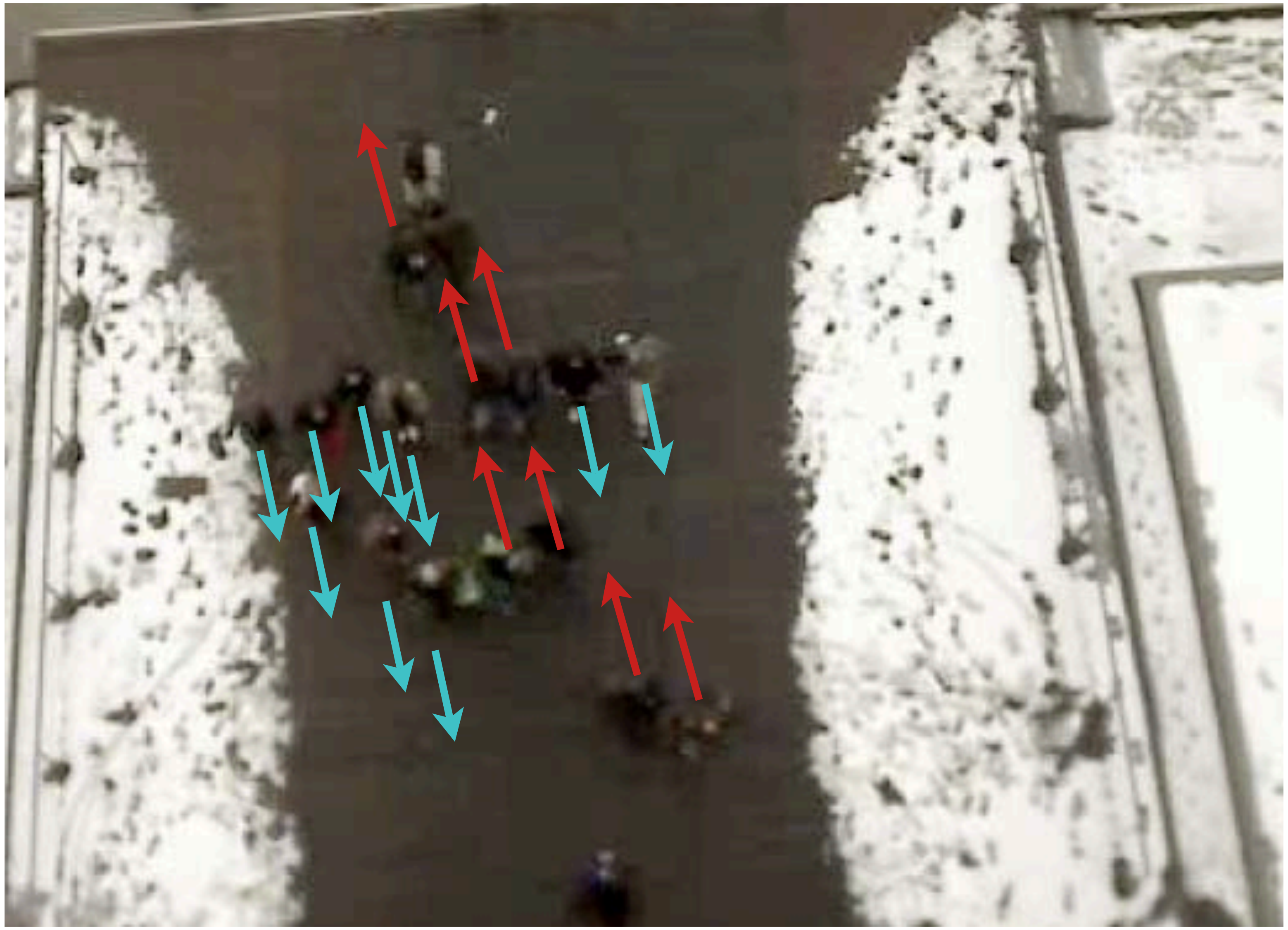


$$(\mathbf{f}^{(R)}, \mathbf{f})^* = \arg\max_{\mathbf{f}^{(R)}, \mathbf{f}} p(\mathbf{f}^{(R)}, \mathbf{f} \mid \mathbf{z}_{1:t})$$

and take $f^{(R)}(t+1)^*$ as the next action in the path

Evaluation: ETH Data Set



- Very dense crowds, large numbers of pedestrians
- Many instances of crowd interaction
- Goal oriented behavior
- Ground truthed for over 8 minutes

Results

Const. covariance *IGP and pedestrian* *IGP and pedestrian*

Const. cov. evasive; IGP similar to pedestrian

Results

Path length vs safety, 10 runs
IGP outperforms pedestrians.
Constant cov inappropriate

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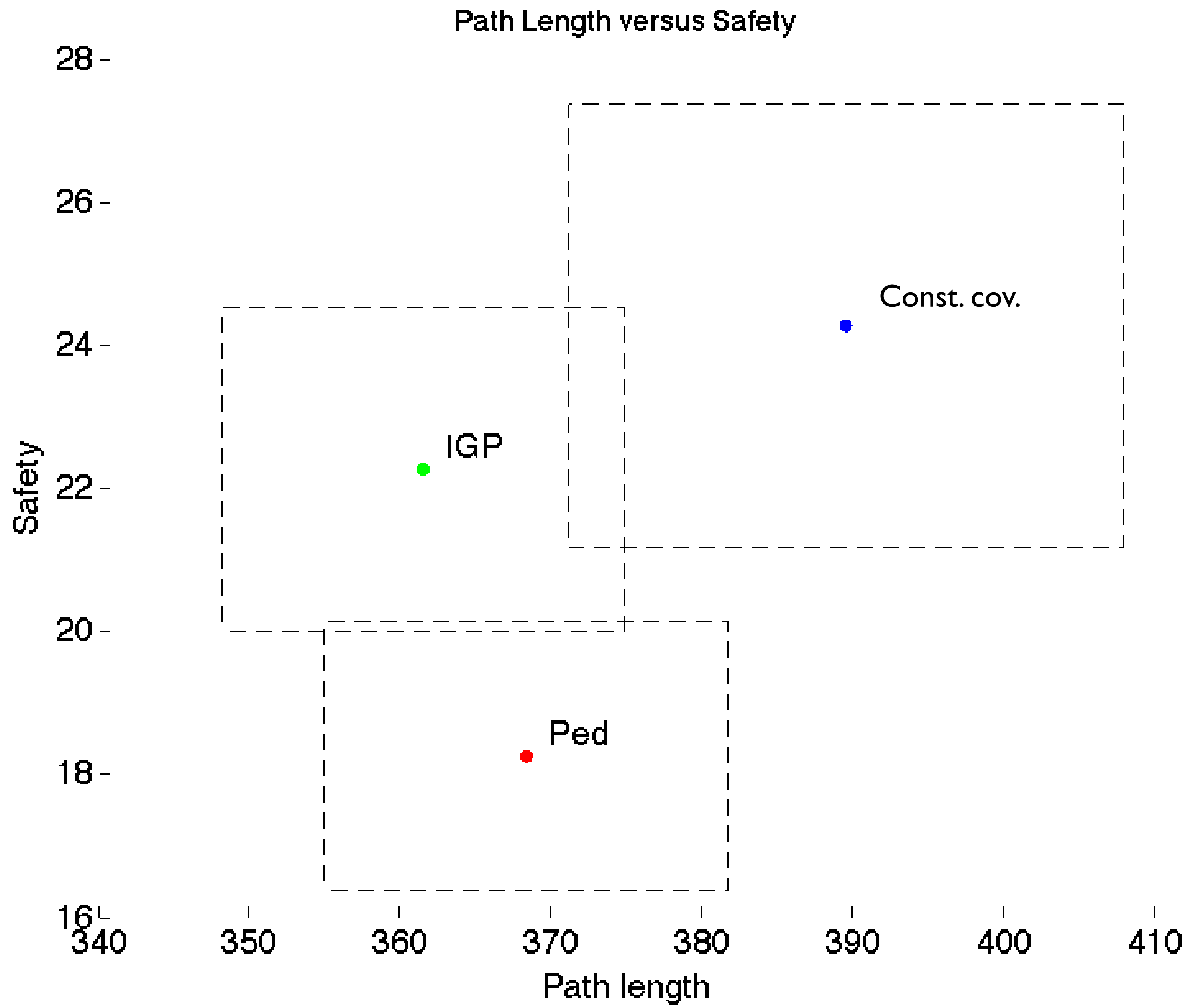

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Runtime in Matlab: $\approx$ 10Hz

Conclusions

- Defined frozen robot problem
- In dense crowds, freezing robot problem occurs if $p(\mathbf{f} \mid \mathbf{z}_{1:t}) = \prod_{i=1}^{n} p(\mathbf{f}^{(i)} \mid \mathbf{z}_{1:t})$ assumed
- Navigation in dense crowds requires interaction modeling
- IGP, a nonparametric statistical model based on dependent output GPs
- Navigation $=$'s inference in this model
- Evaluation on real world pedestrian data
- IGP outperformed pedestrians, state of the art algorithm
- Future: develop experiments for cafeteria at lunchtime