Linking Uncertain Events –

Searching the space of globally feasible explanations

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Outline

- Drop-off and Pick-up Problem
  - Ambiguities
  - Formulating the Problem
- Linking Uncertain Events
  - Labelling a Bayesian Network
  - Searching the space - RJMCMC
- Results
  - Datasets
- Carried Object Detection
  - The method
  - Results

From the news…

- 7/6/2007: York (290 bicycle thefts during May 2007) city sets up CCTV cameras over bicycle racks.
- 22/6/2007: Oxford (1800 bicycle thefts during the last year) city sets up CCTV cameras over bicycle racks.

THE Press

national-lottery.
Players must be 16 or over. Games Rules and Proced

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CCTV cameras at bike racks

By *Helen Gabriel*

POLICE are set to put up spy cameras over York's bike racks in a bid to catch thieves.

The small CCTV cameras will be set up to watch over cycle storage facilities in the city centre in the latest bid to slash the increasing number of bike thefts.

The moveable cameras are the latest in a series of measures being used by police in a bid to reduce bike thefts, with between five bikes being stolen every day in the city.

From the news…

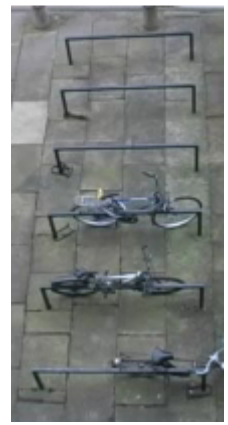
- 23/5/2007 – Catching Daniel Westrop…
  "*have been stealing commuters' cycles, often two a day, for the past three years*"!!

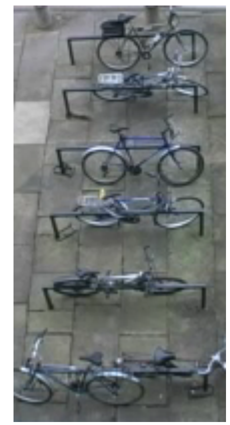
Associating Drop-offs with Pick-ups

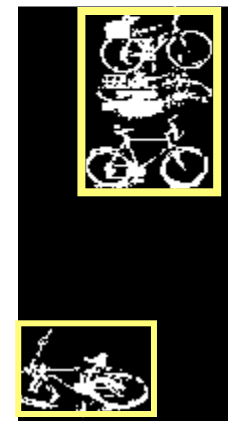
What we see…

Associating Drop-offs with Pick-ups

What the computer sees…







Trajectories

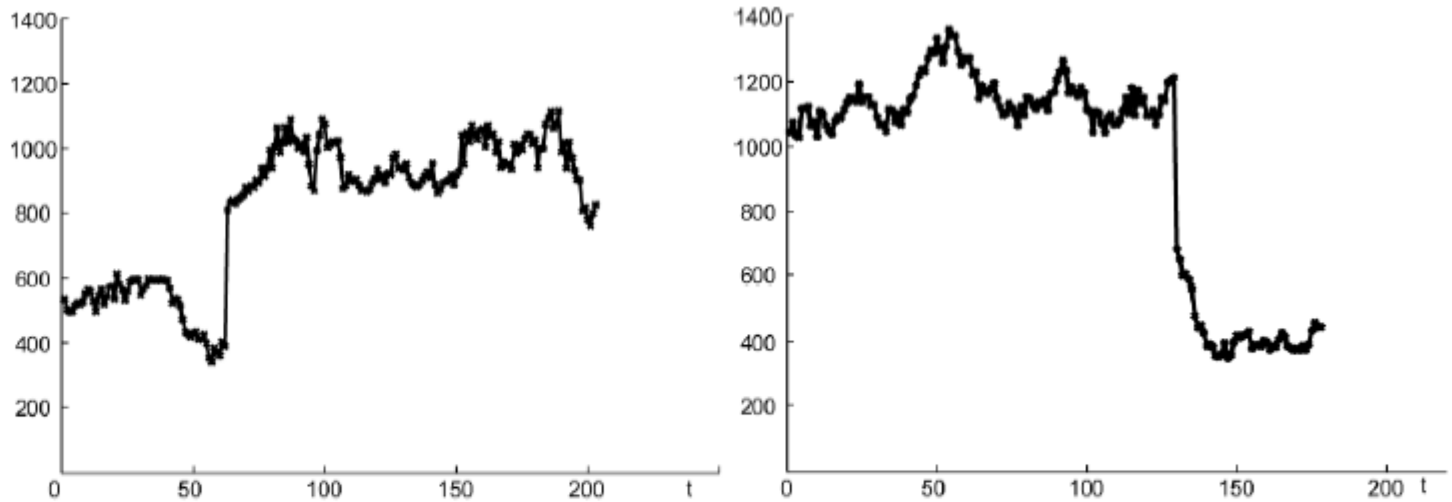
Blobs

Associating Drop-offs with Pick-ups

- The required explanation..
  1. What each person did (drop/pick/pass-by)
  2. Which bicycle did he drop/pick
  3. Try to connect a pick to a previous drop (if observed)

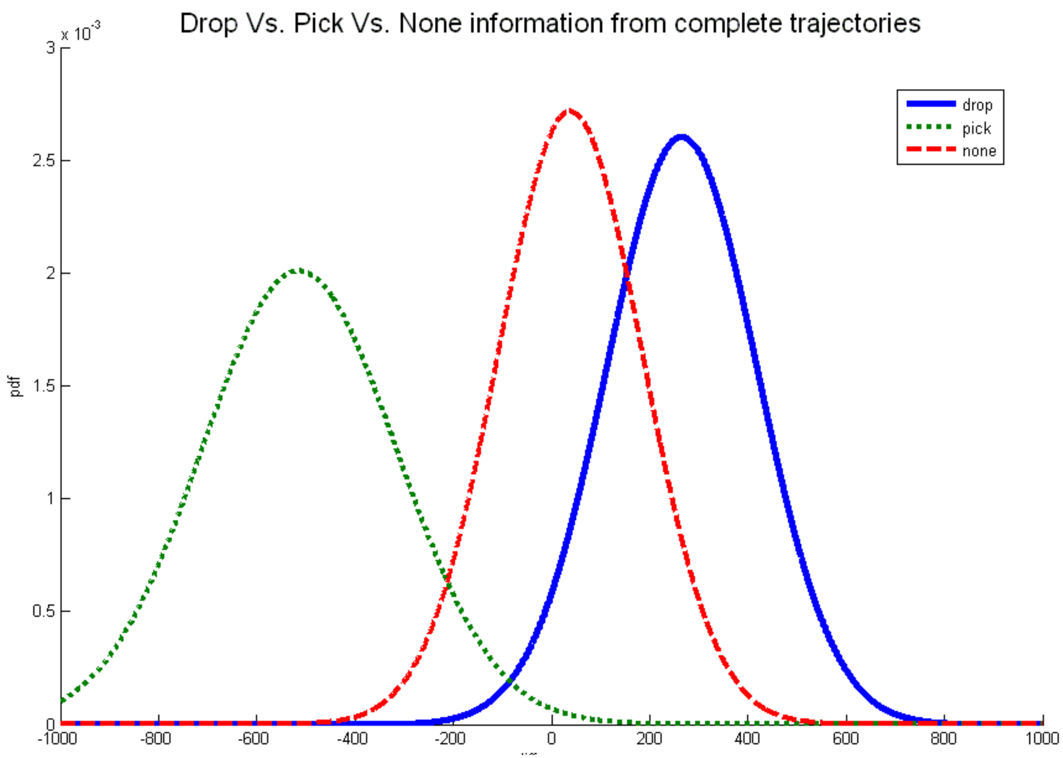
Associating Drop-offs with Pick-ups

1. Deciding on dropping people, picking people and passer bys.



Associating Drop-offs with Pick-ups

1. Deciding on dropping people, picking people and passer bys.



Associating Drop-offs with Pick-ups

2. Linking people to the blobs they interacted with.
    - Spatial Proximity
    - Change in Edge features

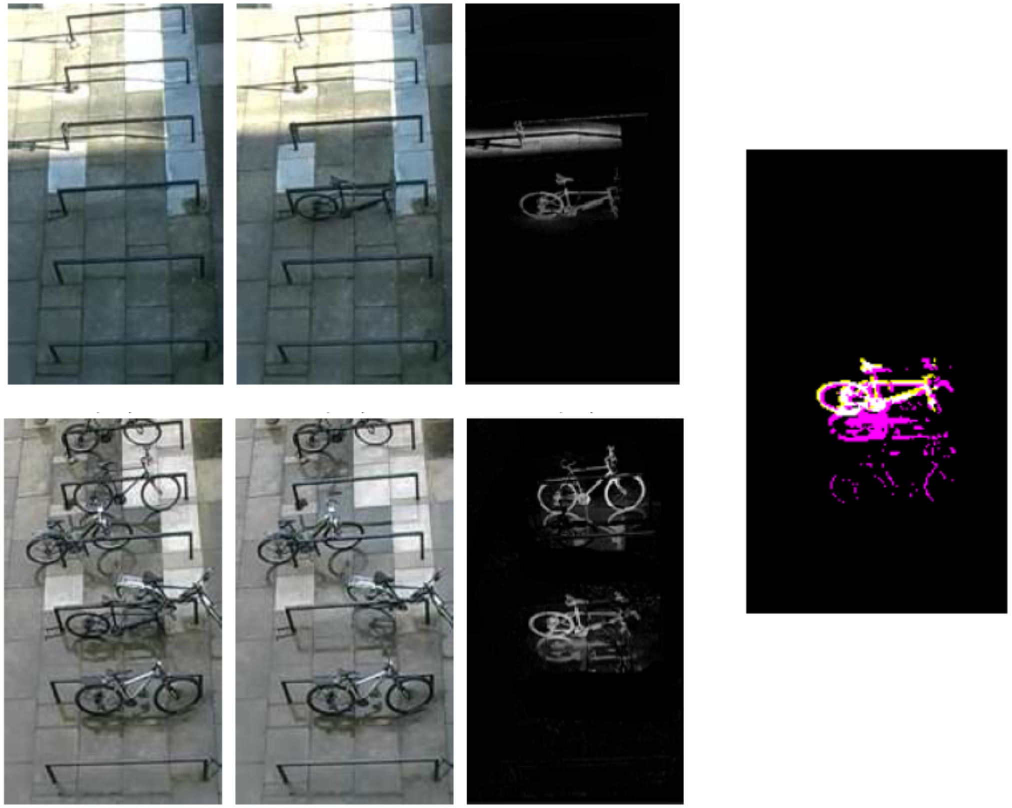
Masked edges

'before' reference image

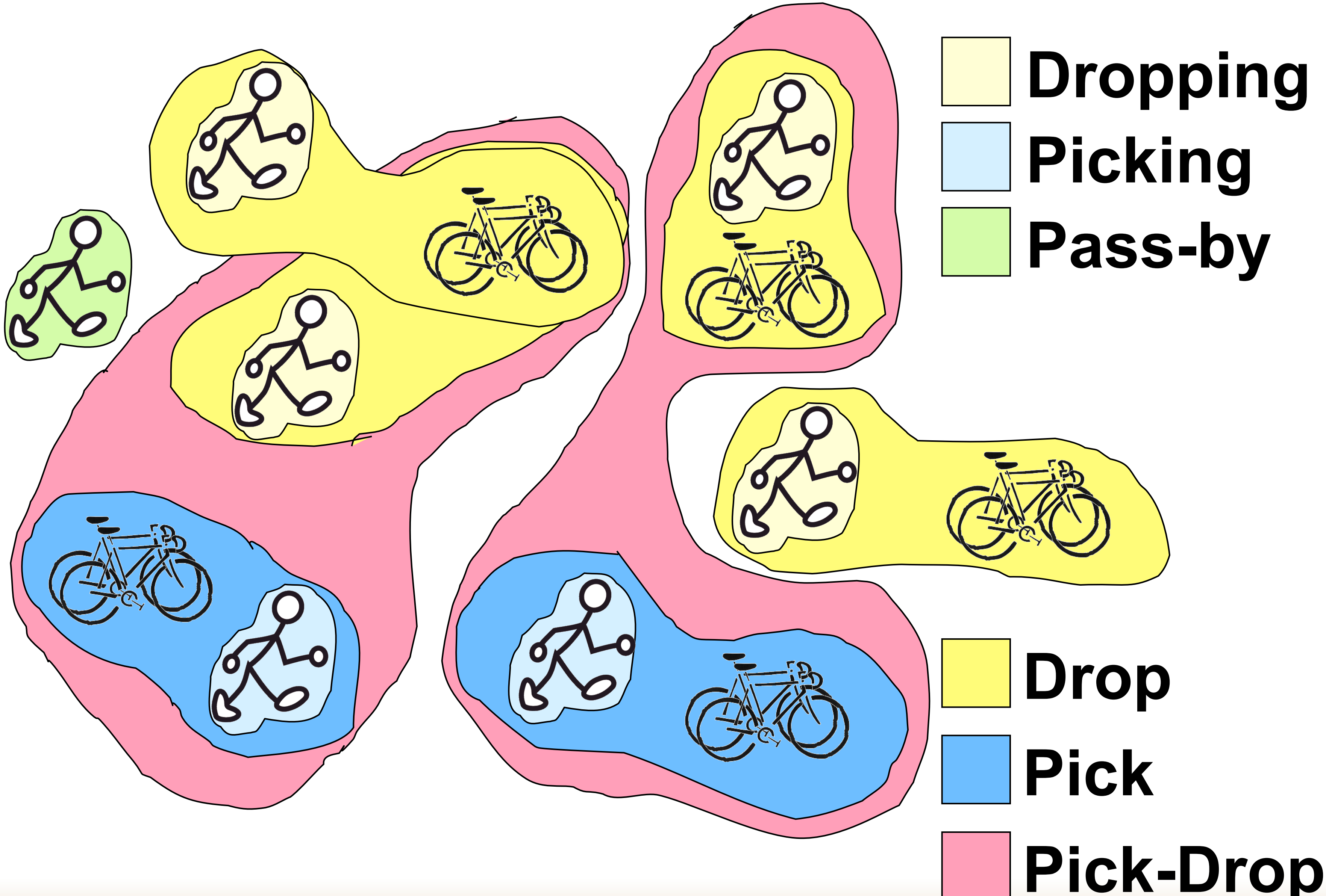
'after' reference image

Associating Drop-offs with Pick-ups

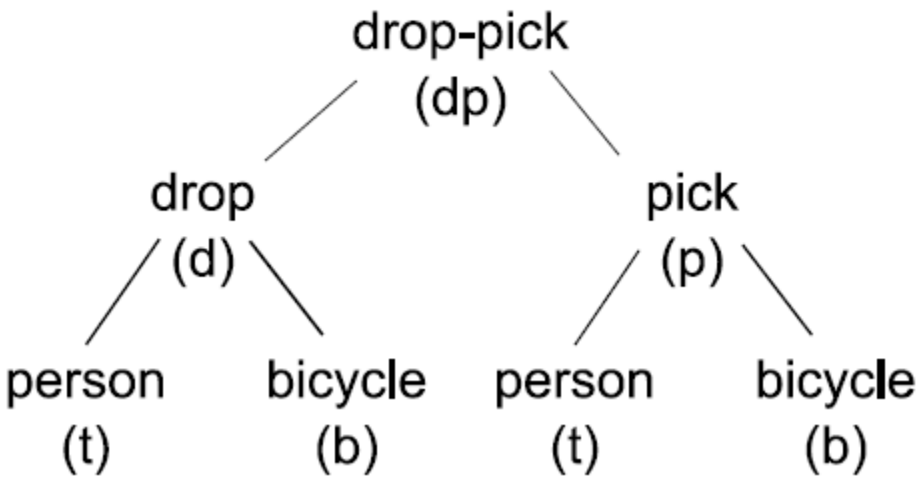
3. Connect drops to picks.
   - Pixel-wise matching of difference masks

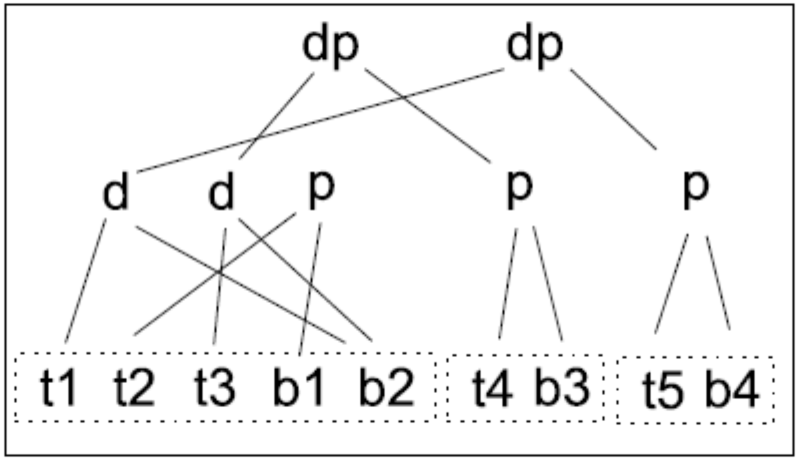


Associating Drop-offs with Pick-ups



Hierarchical Explanation

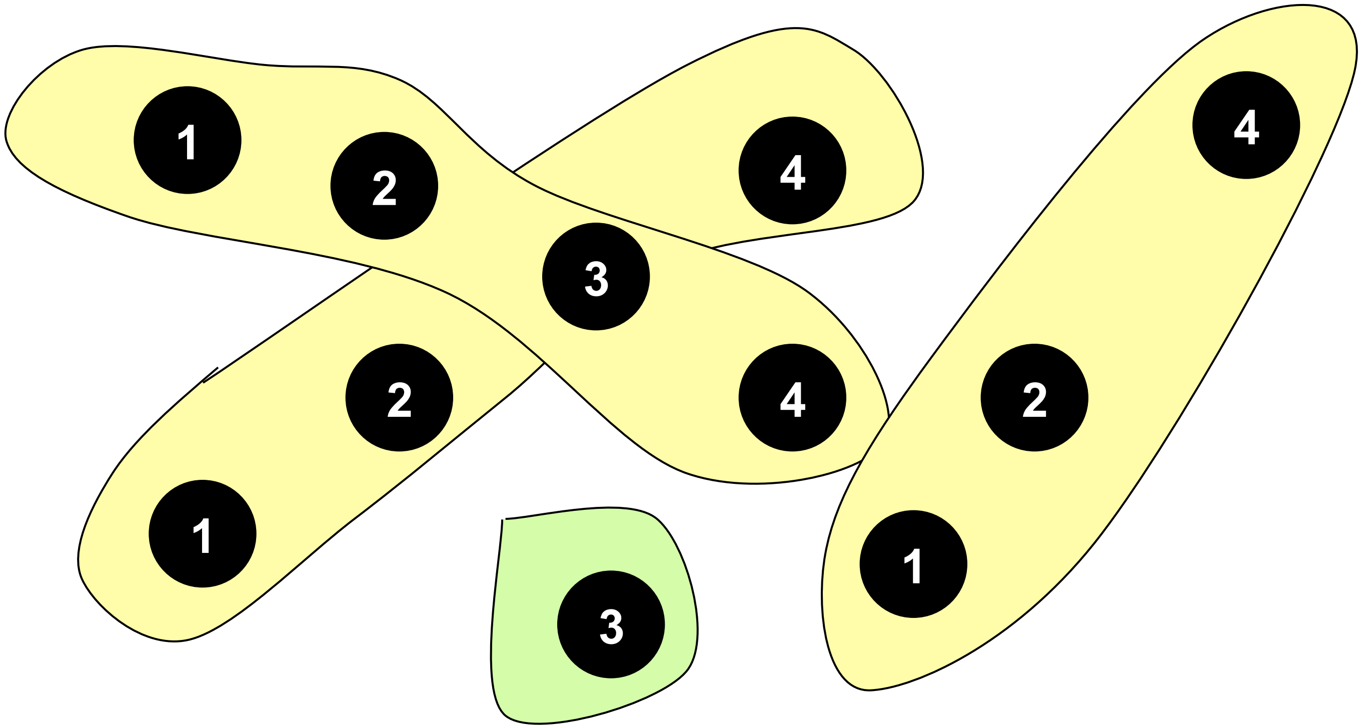




Linking Uncertain Events

- Separately
  - Find the best explanation for each observation
  - Constrained linkage
- Jointly
  - Label and link simultaneously

Similar Work – Radar Surveillance



Similar Work – Radar Surveillance

- Reid (1979) – MHT
- Cox (1993) – Review
  - NN
  - MHT
  - JPDAF
- Poore (1994) – Bayesian MHT
- Oh, Russell, Sastry (2004) - MCMC

Similar Work – Citations Mapping

[Lashkari et al 94] Collaborative Interface Agents, Yezdi Lashkari, Max Metral, and Pattie Maes, Proceedings of the Twelfth National Conference on Articial Intelligence, MIT Press, Cambridge, MA, 1994.

Y. Bar-Shalom and T. E. Fortman. *Tracking and Data Association*. Academic Press, 1988.

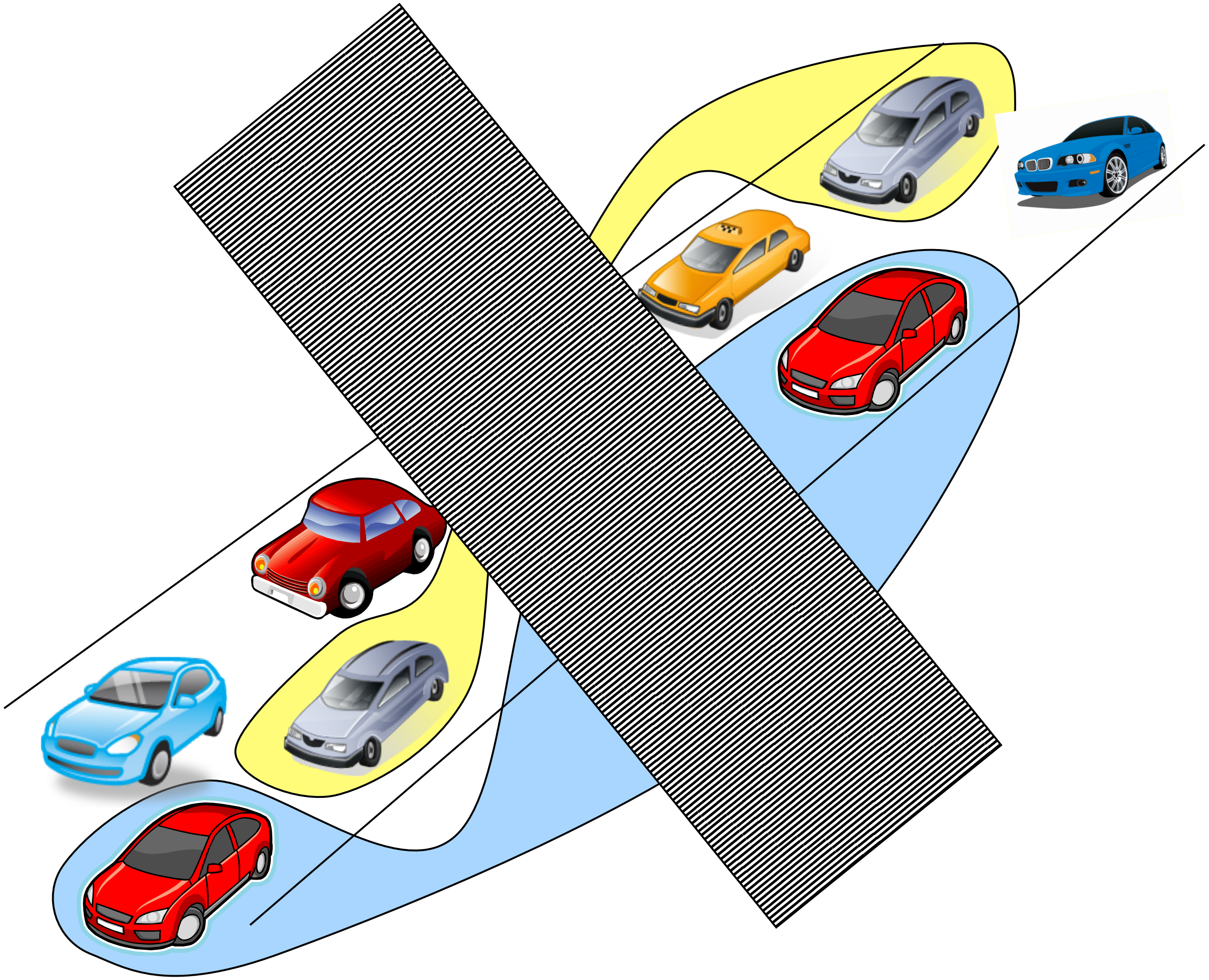
I. J. Cox and S. Hingorani. An effi cient implementation and evaluation of Reid's multiple hypothesis tracking algorithm for visual tracking. In *IAPR-94*, 1994.

H. Pasula, S. Russell, M. Ostland, and Y. Ritov. Tracking many objects with many sensors. In *IJCAI-99*, 1999.

Metral M. Lashkari, Y. and P. Maes. Collaborative interface agents. In Conference of the American Association for Artificial Intelligence, Seattle, WA, August 1994.

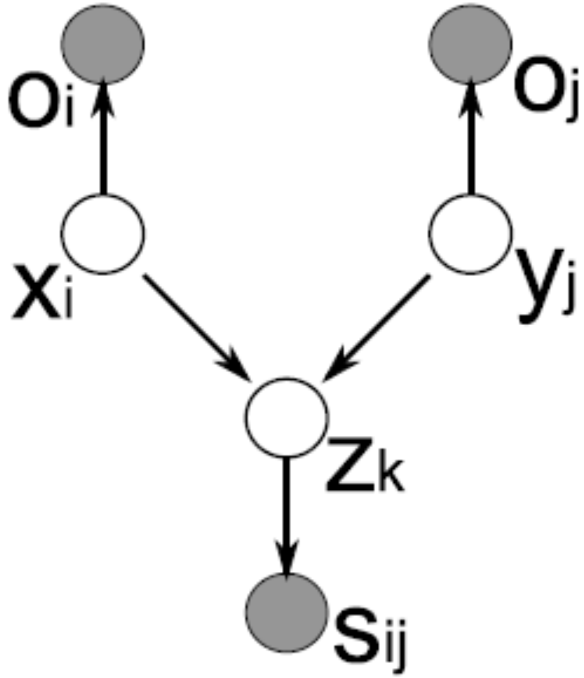
- Pasula et. al. (2003)

Similar Work – Visual Data

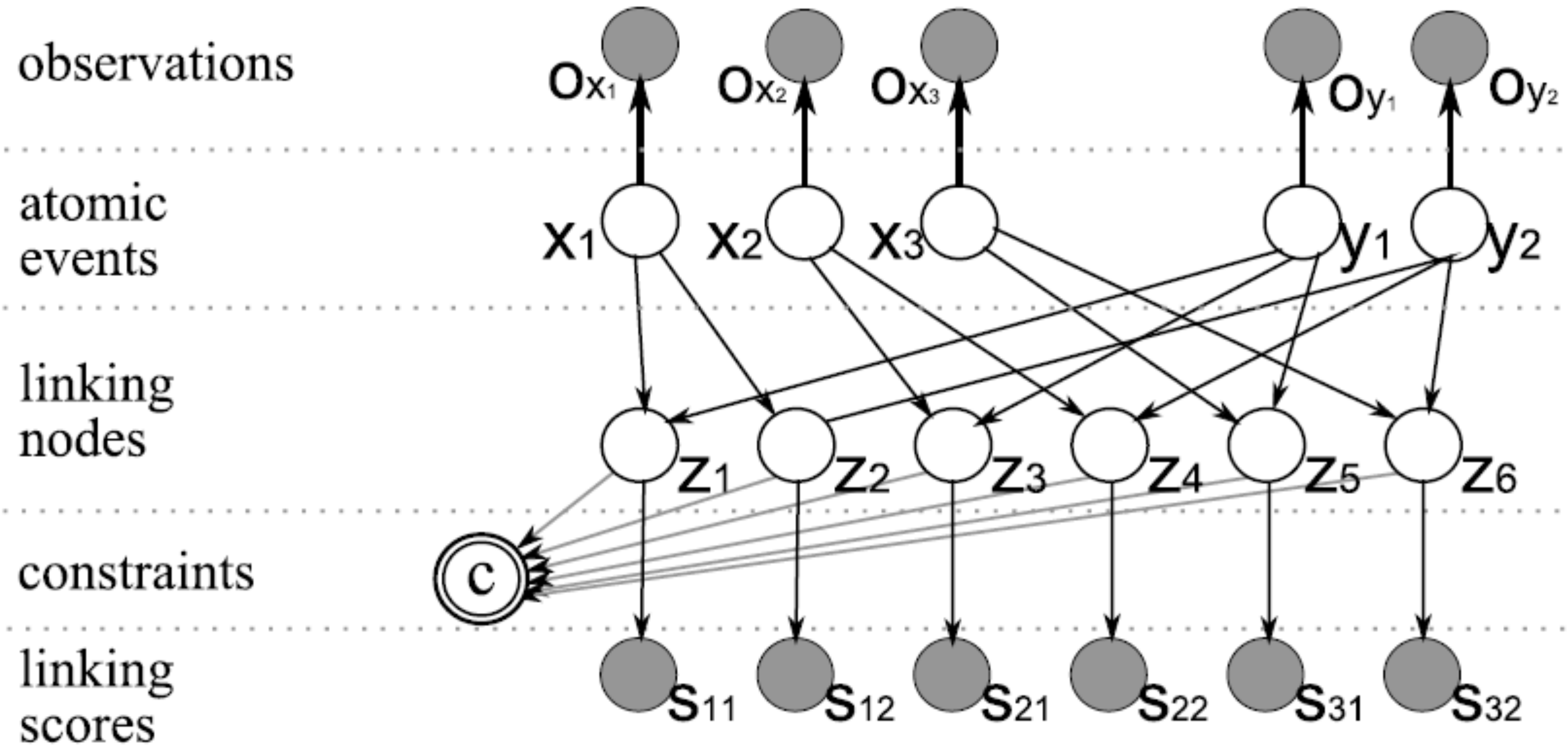


- Huang and Russell (1998), Pasula et. al. (1999)
- Zajdel and Krose (2005)

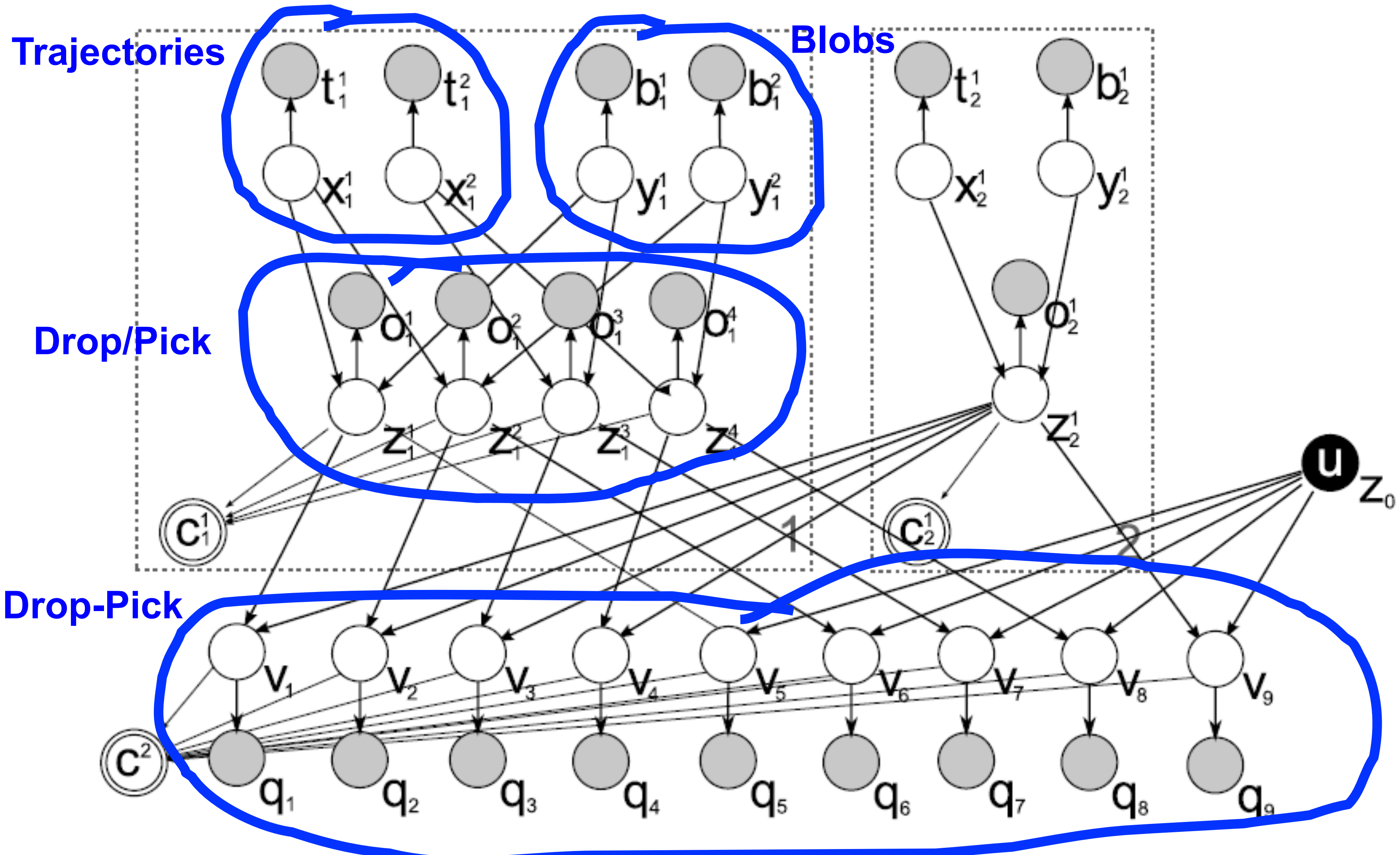
Linking Uncertain Events



Linking Uncertain Events



Linking Uncertain Events



The Bicycles Problem expressed as two-layers linkage

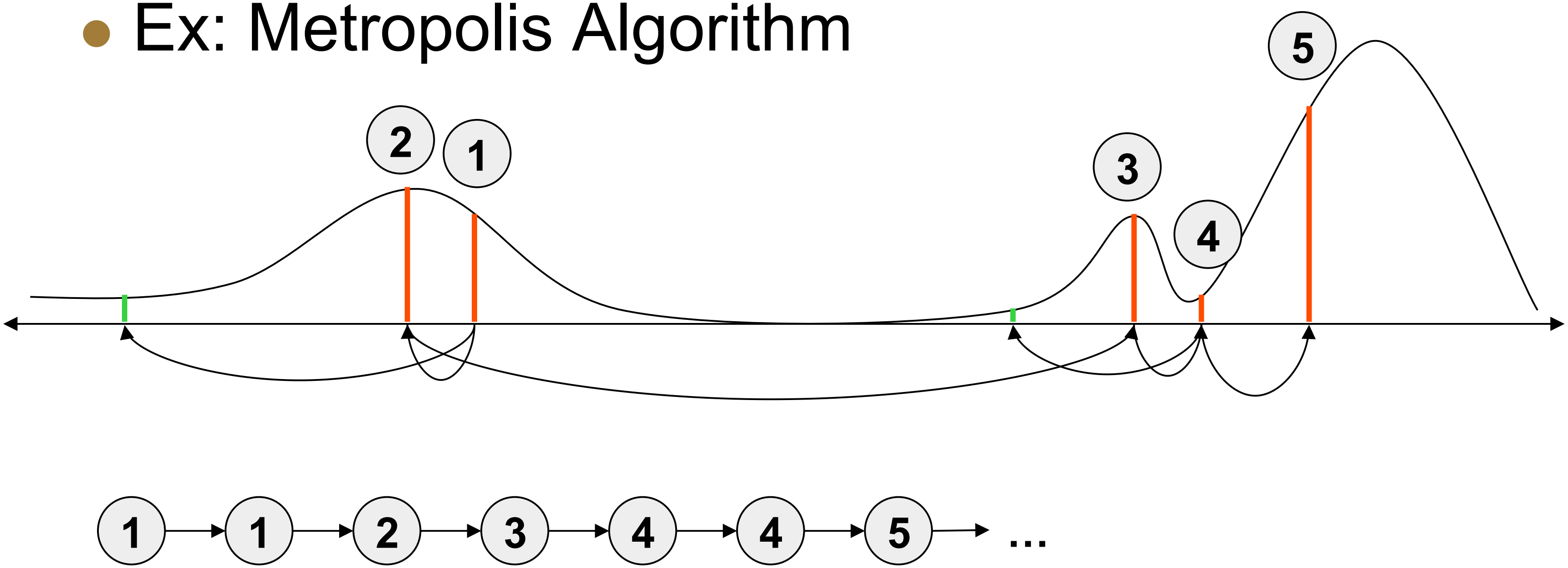
Searching the space of Explanations

$$\omega^\star = \arg\max_{\omega} p(\omega|Y)$$

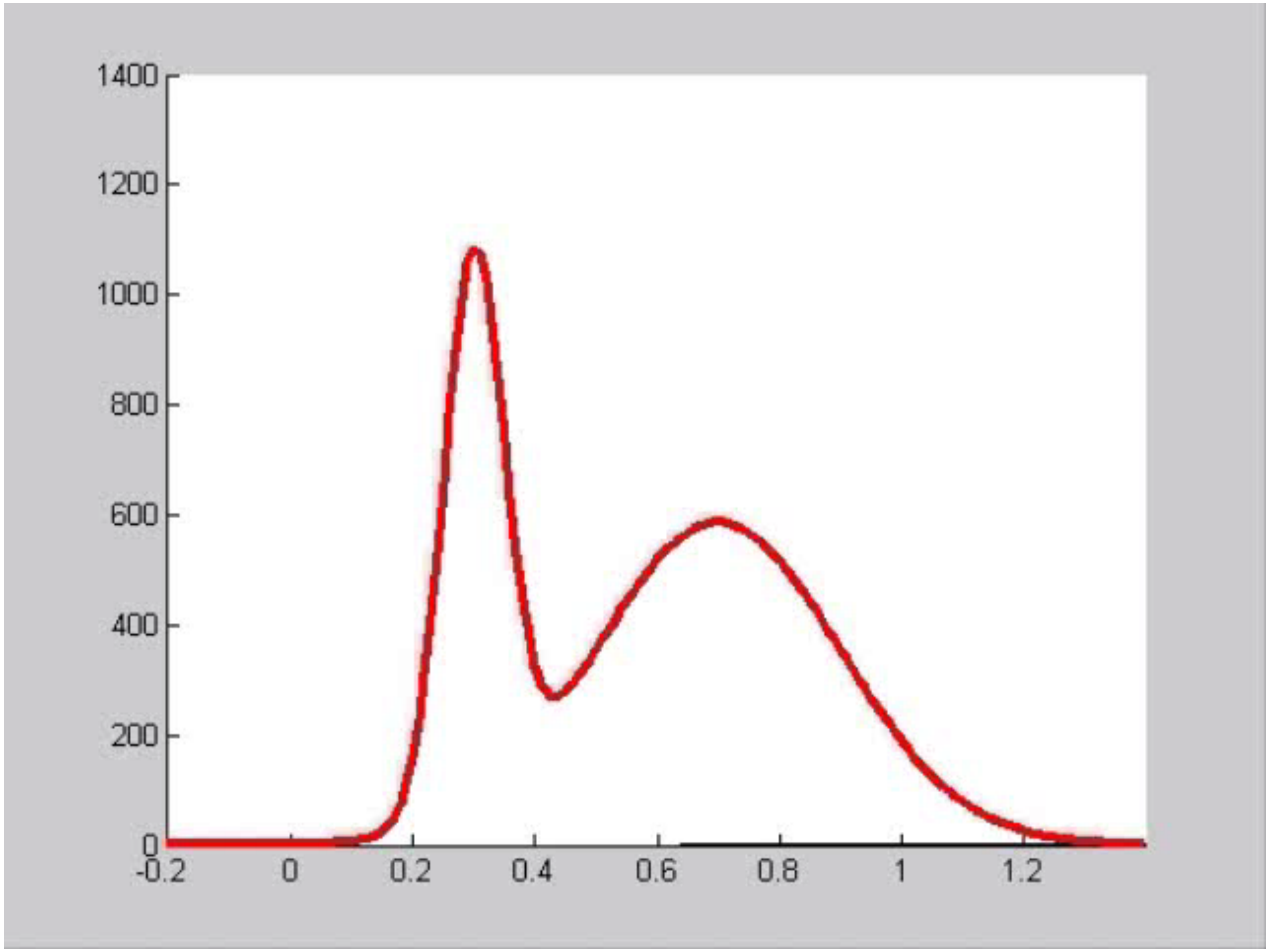
- MCMC samples the space focusing on where posterior is concentrated

Introduction to MCMC

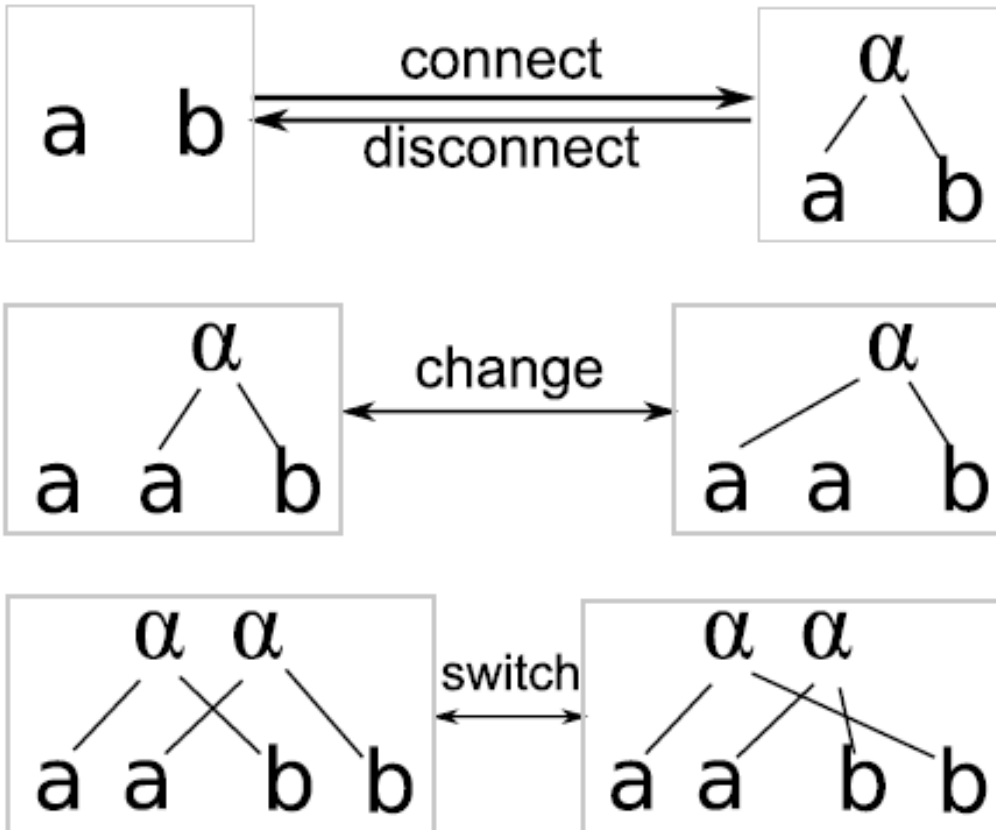
- MCMC – Markov Chain Monte Carlo
- When?
  - You can’t sample from the distribution itself
  - Can evaluate it at any point
  - Ex: Metropolis Algorithm



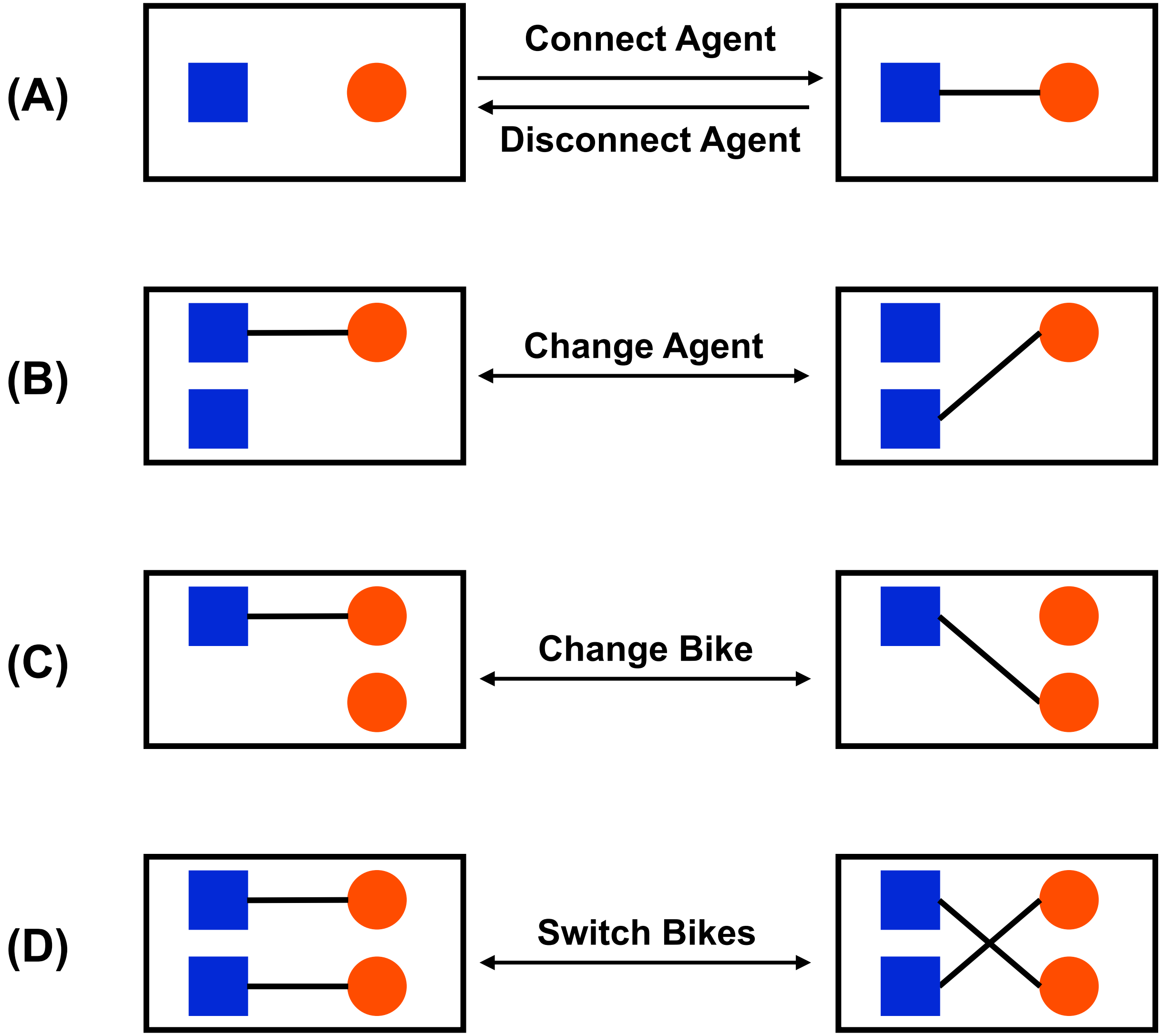
Introduction to MCMC



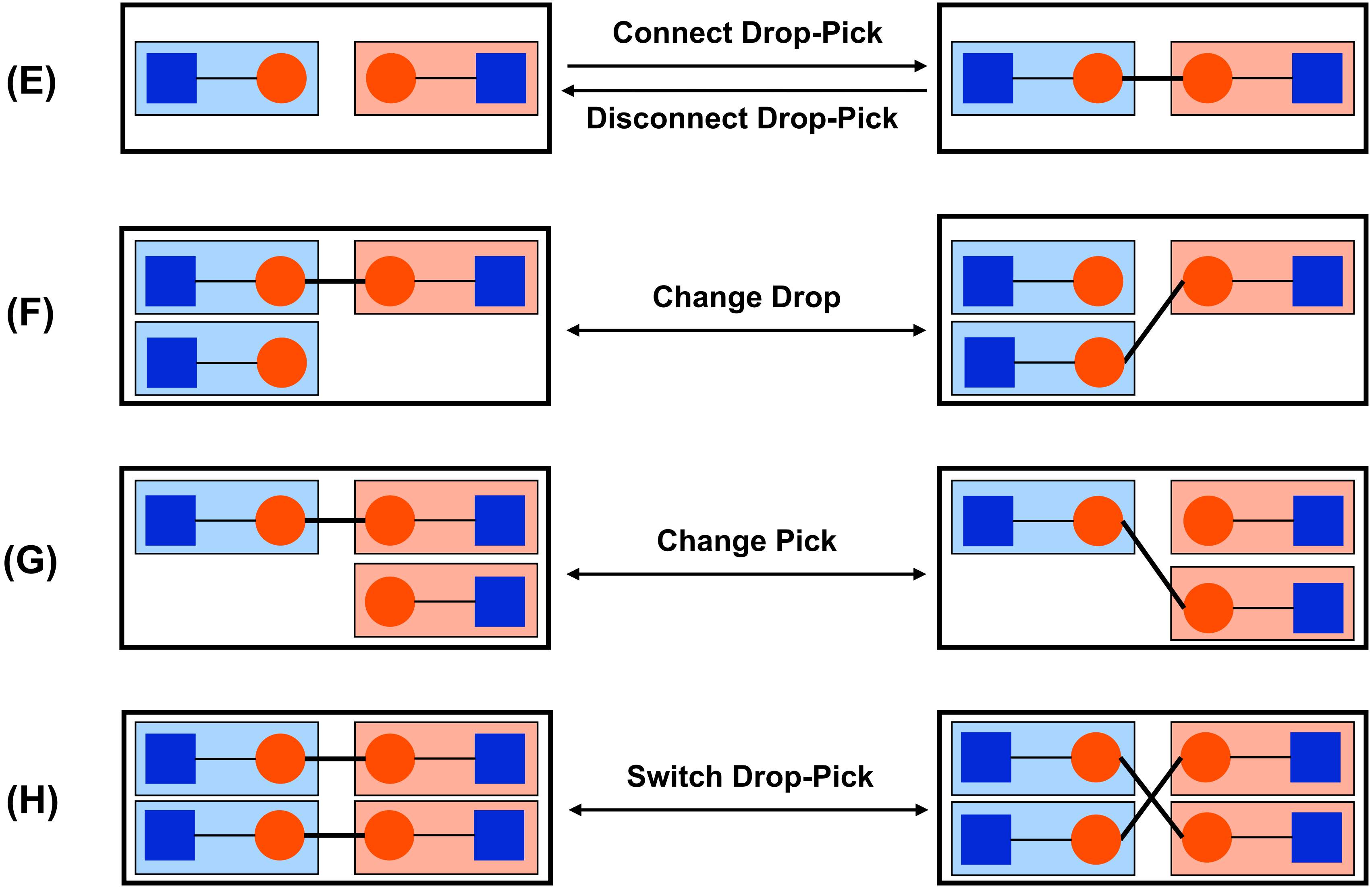
Suggested Moves



Suggested Moves – Bicycles 1



Suggested Moves – Bicycles 2



MCMC General Algorithm

```
                              Markov Chain Monte Carlo
initialize ω_0

for i = 1 to n_mc
  sample m from ξ_i
  sample ω* from Q_m(ω*|ω_{i-1})

  calculate α(ω*|ω_{i-1}) = (π(ω*)/π(ω)) Q(ω|ω*)/Q(ω*|ω)
  sample u from U[0,1]
  if u < α(ω*|ω_{i-1})
    ω_i = ω*
  else
    ω_i = ω_{i-1}
```

initialize ω_0

for i = 1 to n_{mc}

sample m from ξ_i

sample $\omega^\star$ from $Q_m(\omega^\star|\omega_{i-1})$

calculate $\alpha(\omega^\star|\omega_{i-1}) = \left(\frac{\pi(\omega^\star)}{\pi(\omega)}\right) \quad \frac{Q(\omega|\omega^\star)}{Q(\omega^\star|\omega)}$

sample u from $\mathscr{U}[0,1]$

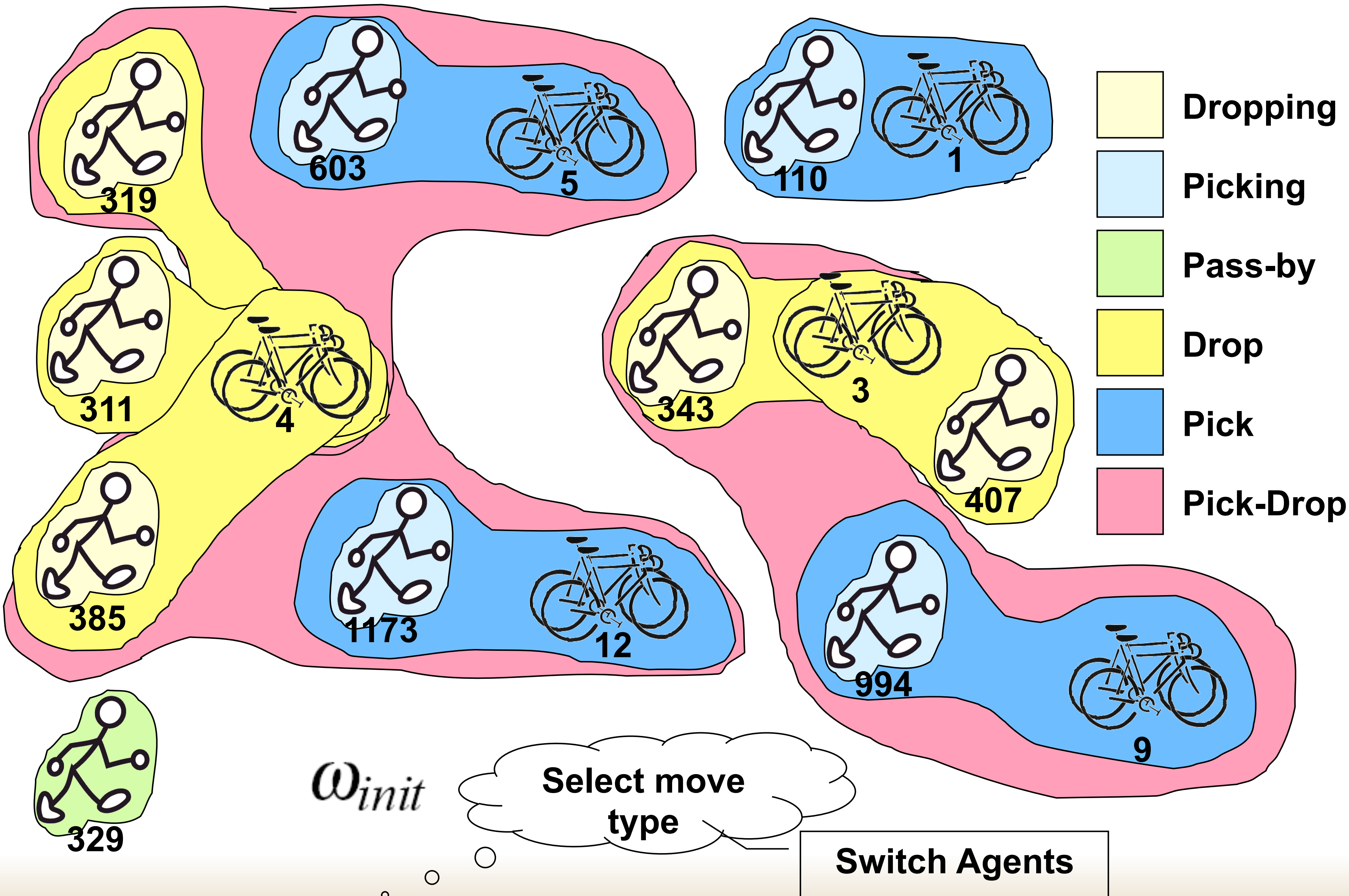
if u < $\alpha(\omega^\star|\omega_{i-1})$

$\omega_i = \omega^\star$

else

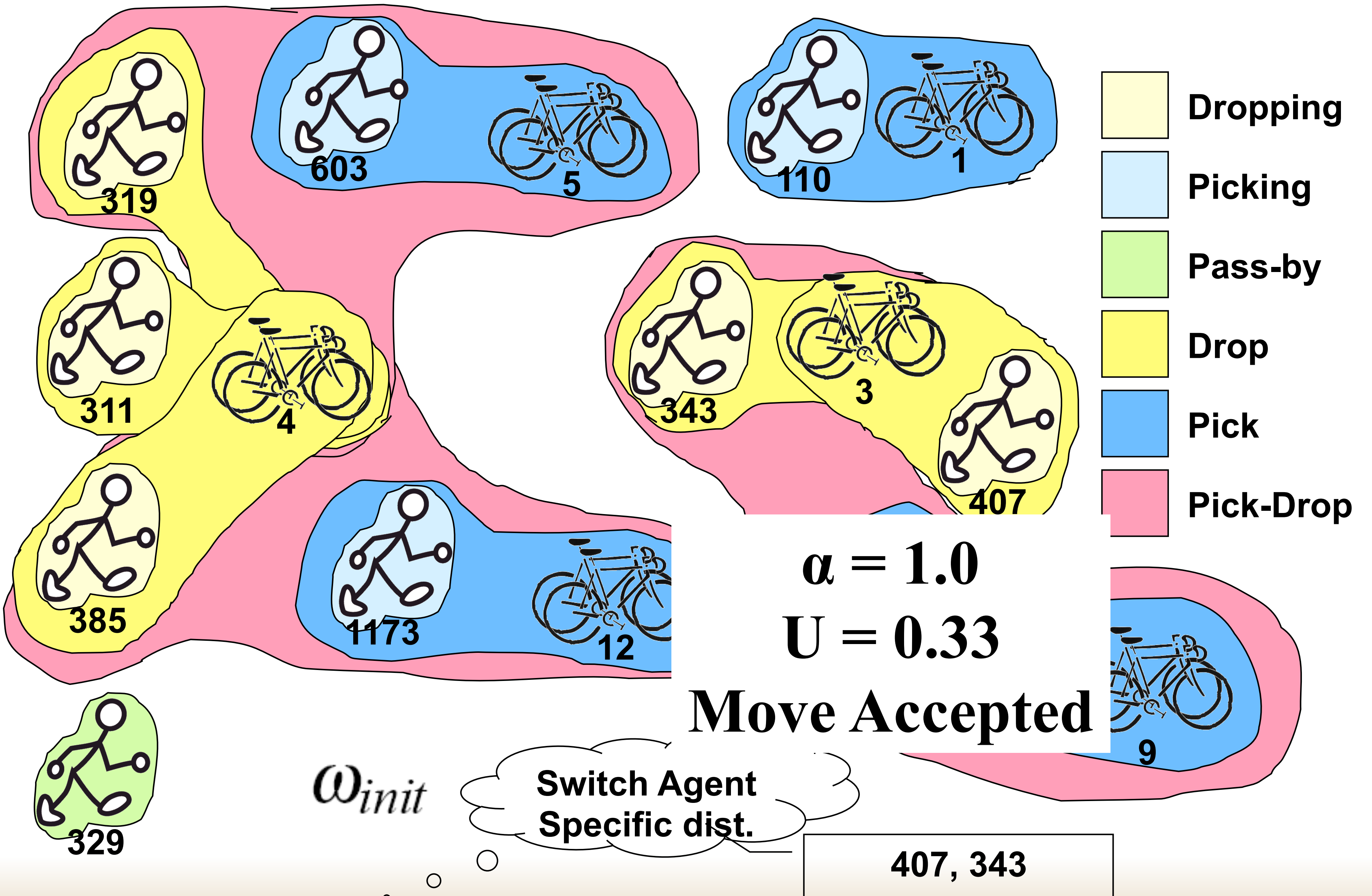
$\omega_i = \omega_{i-1}$

Examples



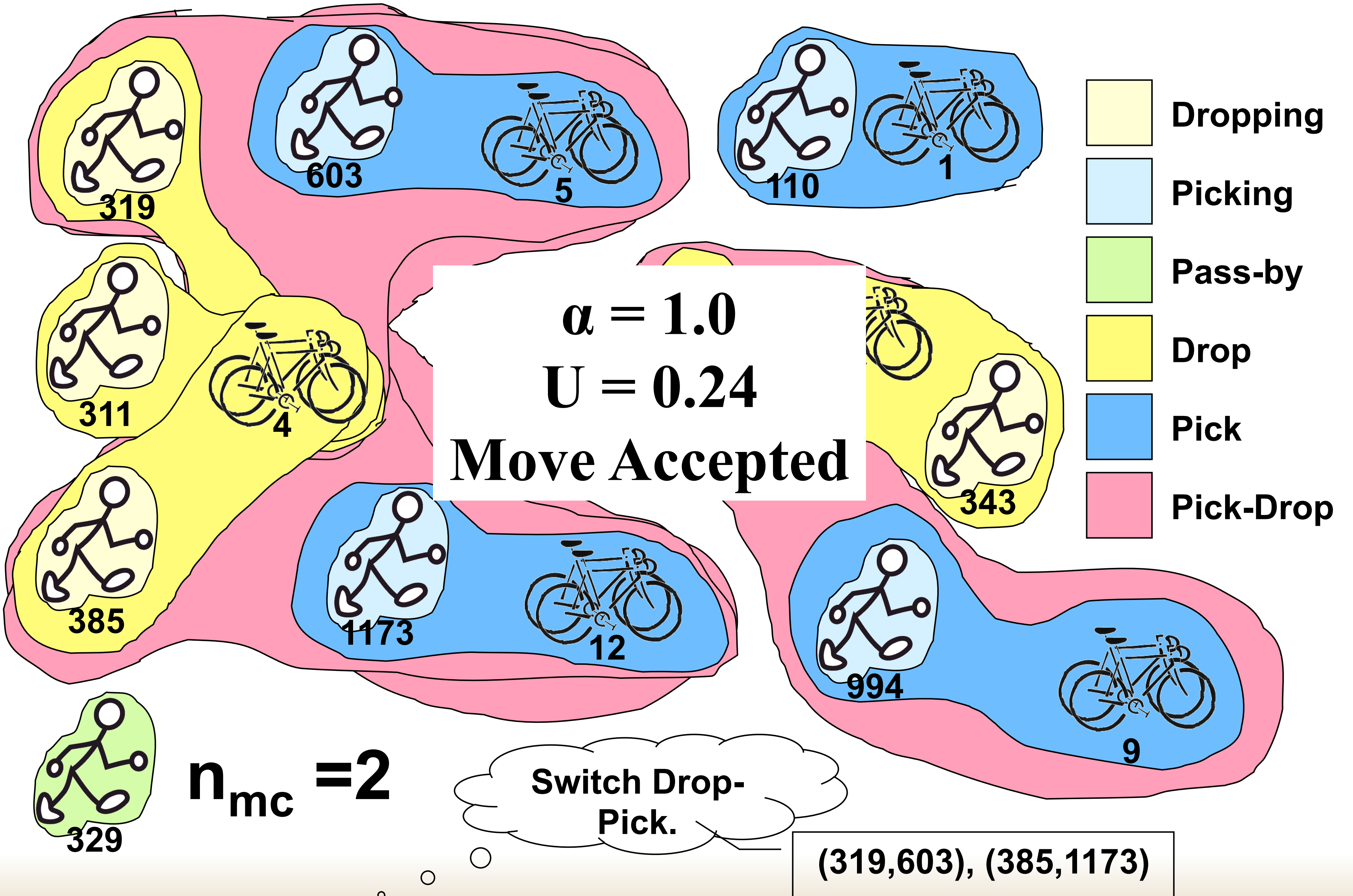
319
603
5
110
1
311
4
343
3
407
385
1173
12
994
9
329
ω_{init}
Select move type
Switch Agents
Dropping
Picking
Pass-by
Drop
Pick
Pick-Drop

Examples

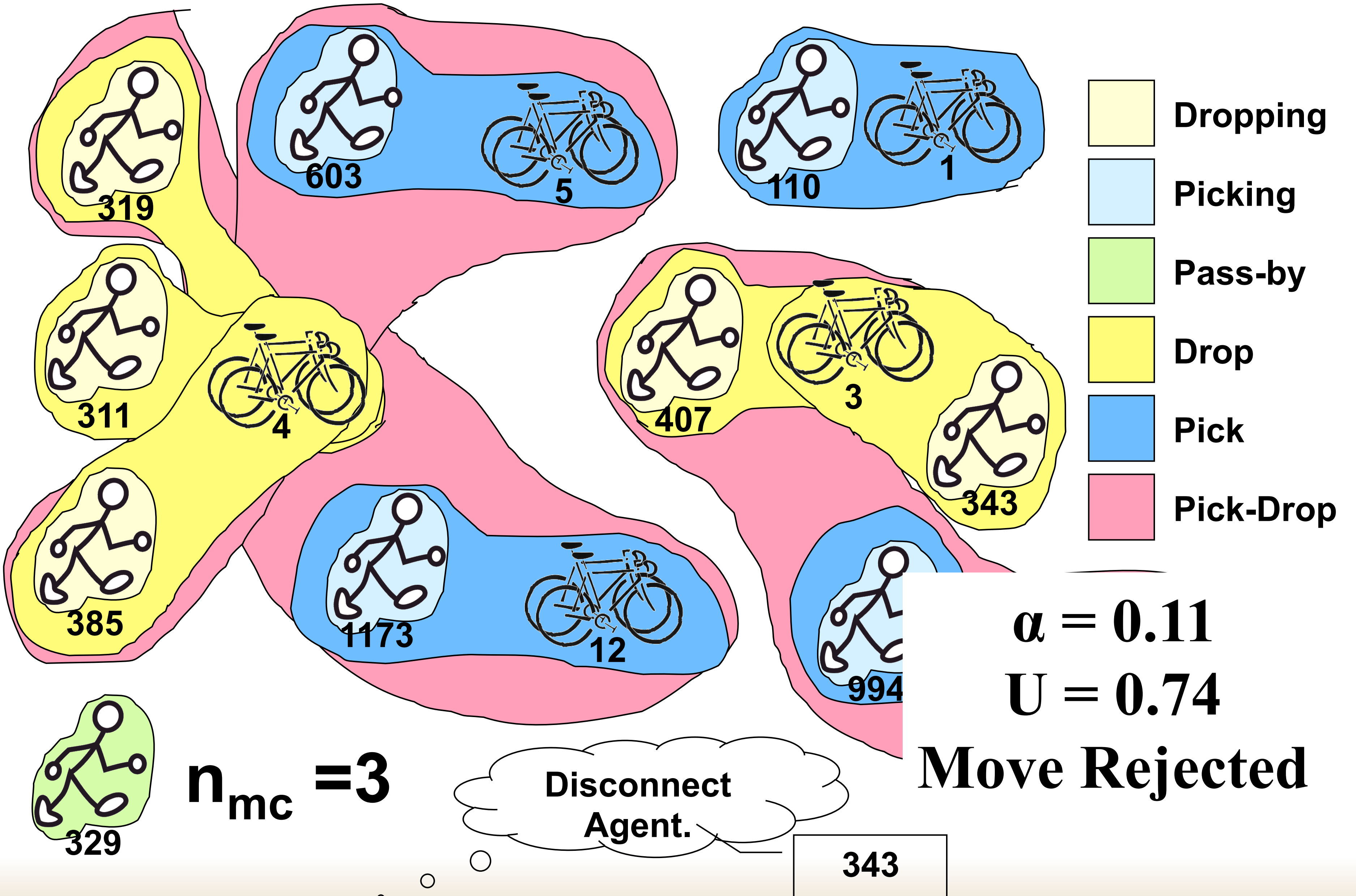


603
5
110
1
319
311
4
343
3
407
385
1173
12
9
329
Dropping
Picking
Pass-by
Drop
Pick
Pick-Drop
$\alpha = 1.0$
$U = 0.33$
Move Accepted
ω_{init}
Switch Agent
Specific dist.
407, 343

Examples


319
603
5
110
1
311
4
385
1173
12
343
994
9
329
Dropping
Picking
Pass-by
Drop
Pick
Pick-Drop
α = 1.0
U = 0.24
Move Accepted
n_{mc} =2
Switch Drop-Pick.
(319,603), (385,1173)

Examples



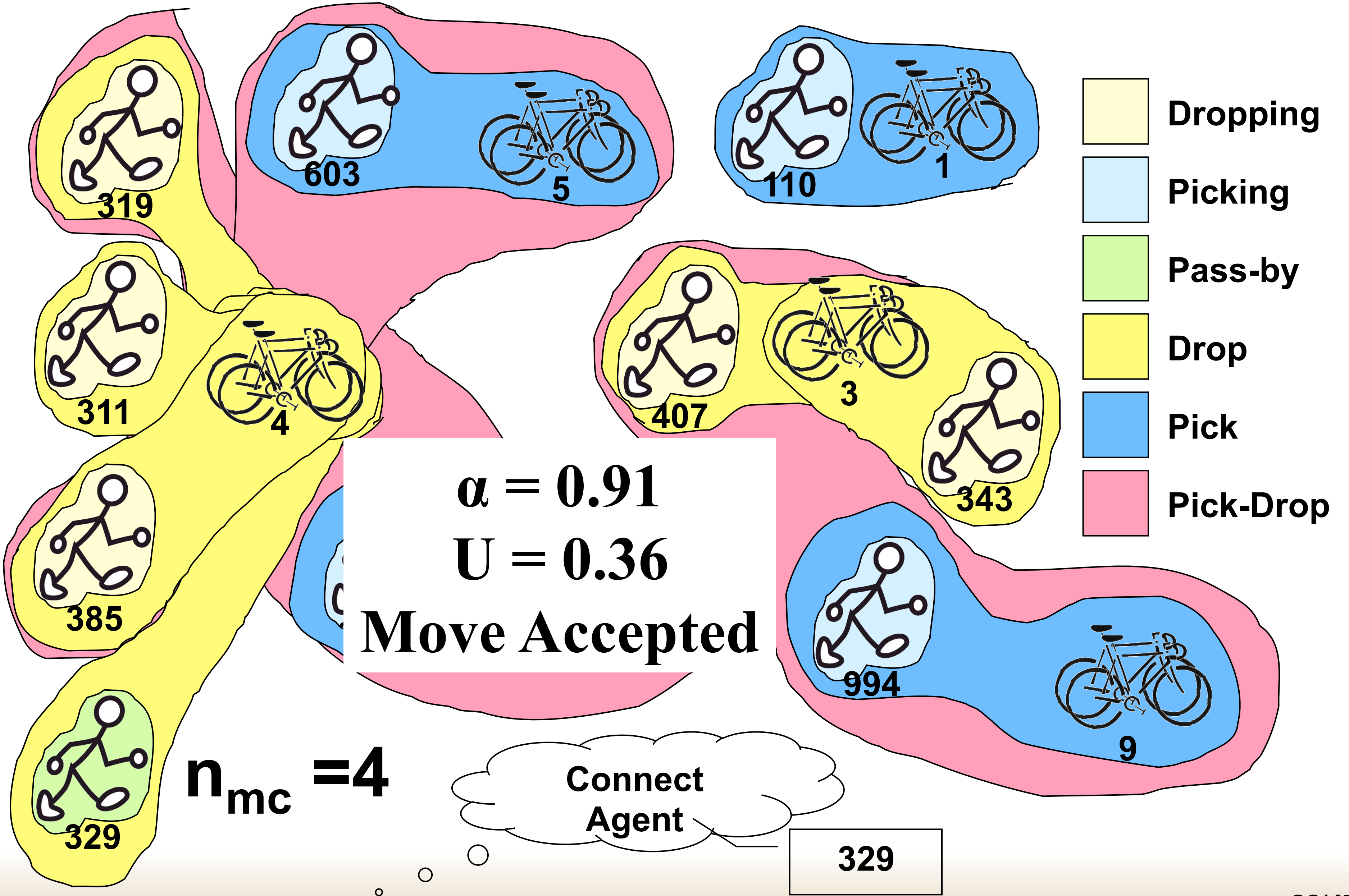
$n_{mc} = 3$

$\alpha = 0.11$

$U = 0.74$

Move Rejected

Examples



$\alpha = 0.91$

$U = 0.36$

Move Accepted

$n_{mc} = 4$

MCMC General Algorithm

Markov Chain Monte Carlo

```
initialize ω_0

for i = 1 to n_mc
  sample m from ξ_i
  sample ω* from Q_m(ω*|ω_{i-1})

  calculate α(ω*|ω_{i-1}) = (π(ω*)/π(ω)) (Q(ω|ω*)/Q(ω*|ω))
  sample u from U[0,1]
  if u < α(ω*|ω_{i-1})
    ω_i = ω*
  else
    ω_i = ω_{i-1}
```

In math notation:

initialize ω_0

for i = 1 to n_{mc}

  sample m from ξ_i

  sample $\omega^\star$ from $Q_m(\omega^\star|\omega_{i-1})$

  calculate $\alpha(\omega^\star|\omega_{i-1}) = \left(\frac{\pi(\omega^\star)}{\pi(\omega)}\right) \quad \frac{Q(\omega|\omega^\star)}{Q(\omega^\star|\omega)}$

  sample u from $\mathscr{U}[0,1]$

  if u < $\alpha(\omega^\star|\omega_{i-1})$

    $\omega_i = \omega^\star$

  else

    $\omega_i = \omega_{i-1}$

Dataset

Dataset

	1	2	3	4	5	6	7
Duration	1h	1h	11h	12h	12h	15h	15h
Drops	24	11	20	20	14	28	39
Picks	20	12	19	10	13	17	41
Drop-picks	20	11	18	20	13	14	22

Results

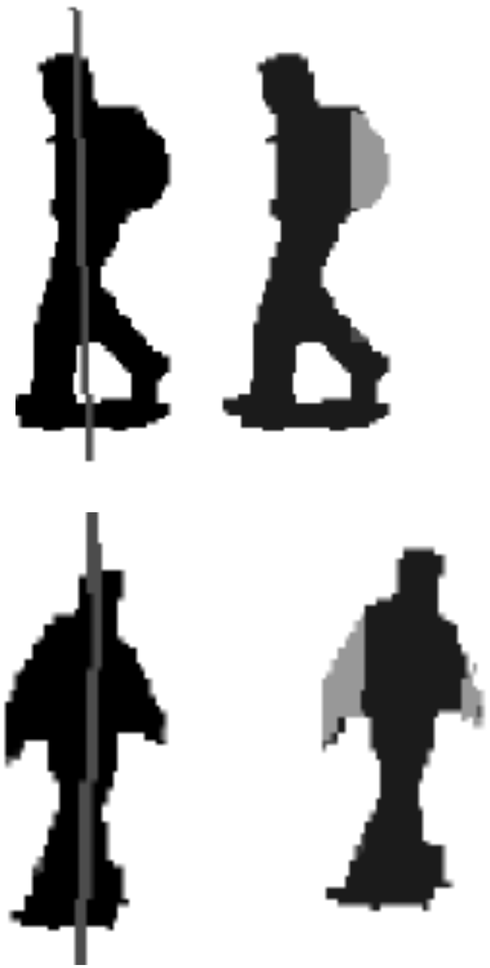
Results

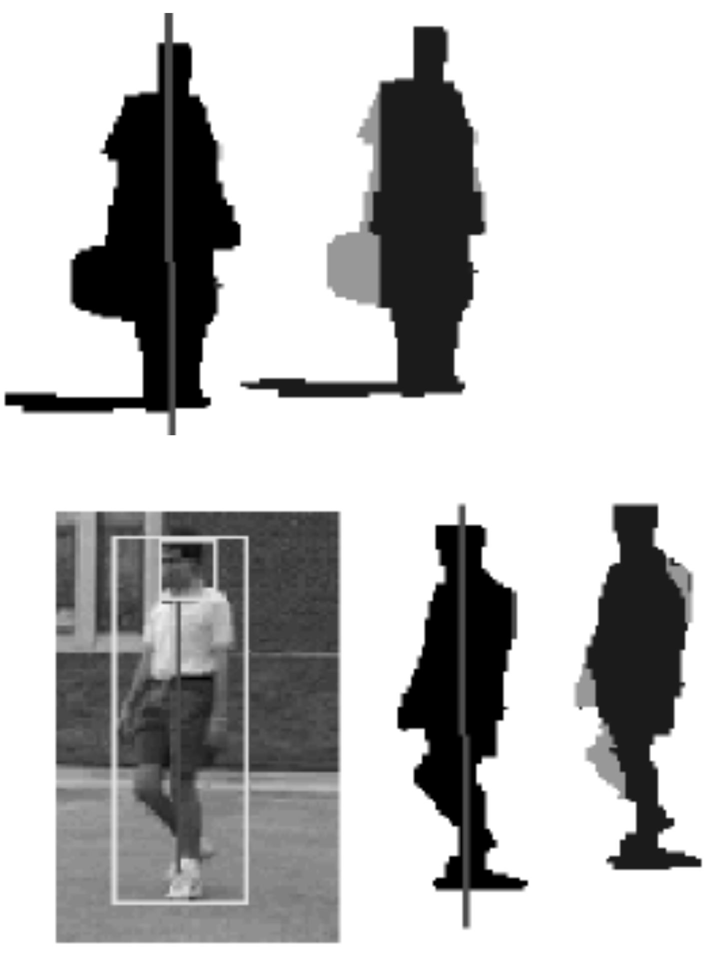
	Split		MCMC		SAMCMC	
	MAP	ACC	MAP	ACC	MAP	ACC
1	102.3	**72.41**	57.9	**91.38**	57.9	**91.38**
2	23.5	**85.19**	4.6	**100.00**	4.6	**100.00**
3	609.7	**58.59**	429.0	**88.28**	422.3	**89.84**
4	6272.7	**73.81**	6077.3	**83.33**	6083.7	**87.30**
5	5034.5	**89.05**	4944.7	**94.89**	4937.1	**94.16**
6	860.4	**66.07**	815.8	**71.43**	808.4	**76.79**
7	934.4	**45.69**	681.2	**48.22**	658.23	**51.78**

Detecting carried objects from Silhouettes

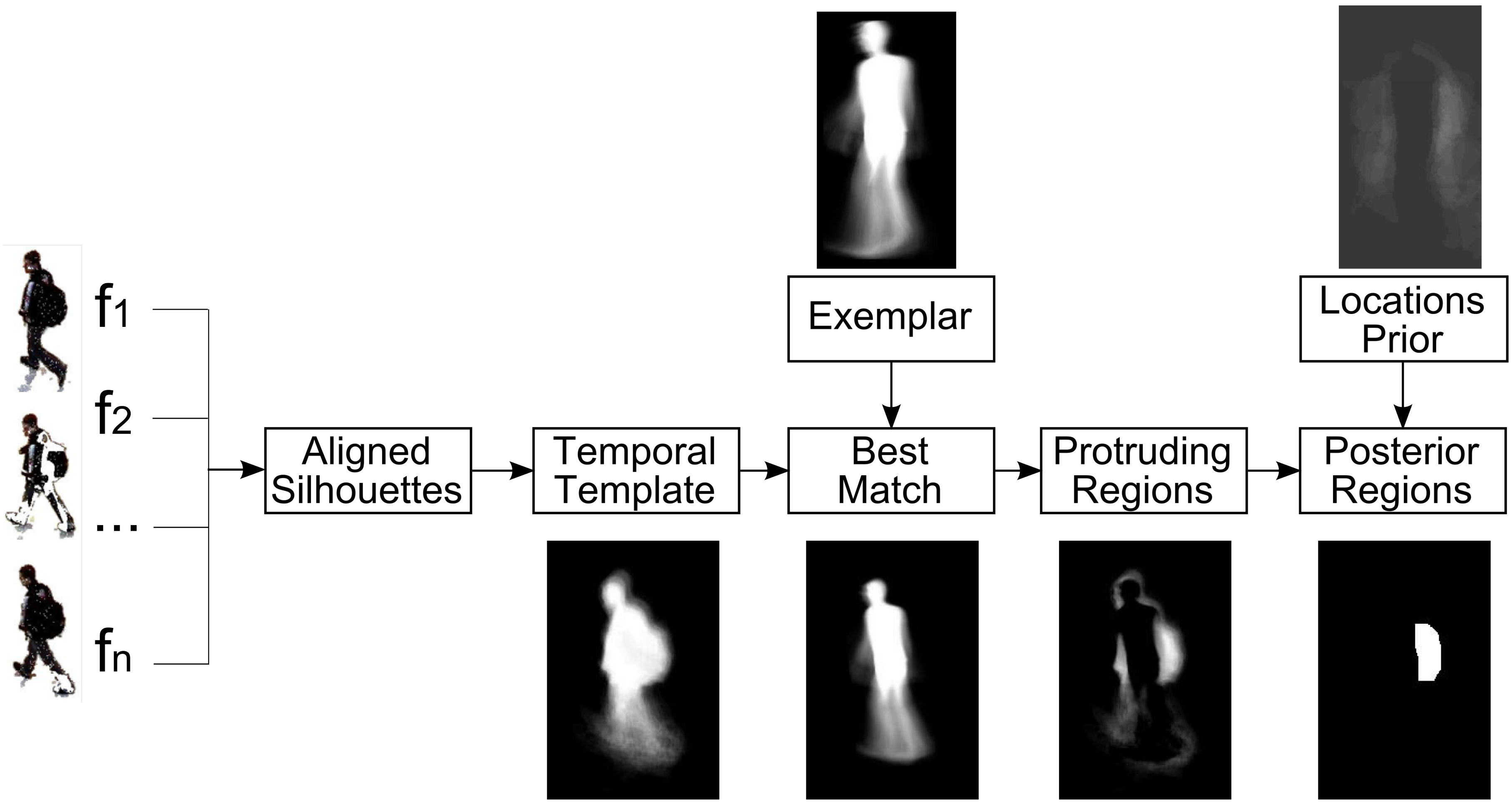
I. Haritaoglu, R. Cutler, D. Harwood, and L. S. Davis. **Backpack: detection of people carrying objects using silhouettes**. In *Proc. Int. Conf. on Computer Vision (ICCV)*, volume 1, pages 102–107, 1999.

Haritaoglu's work





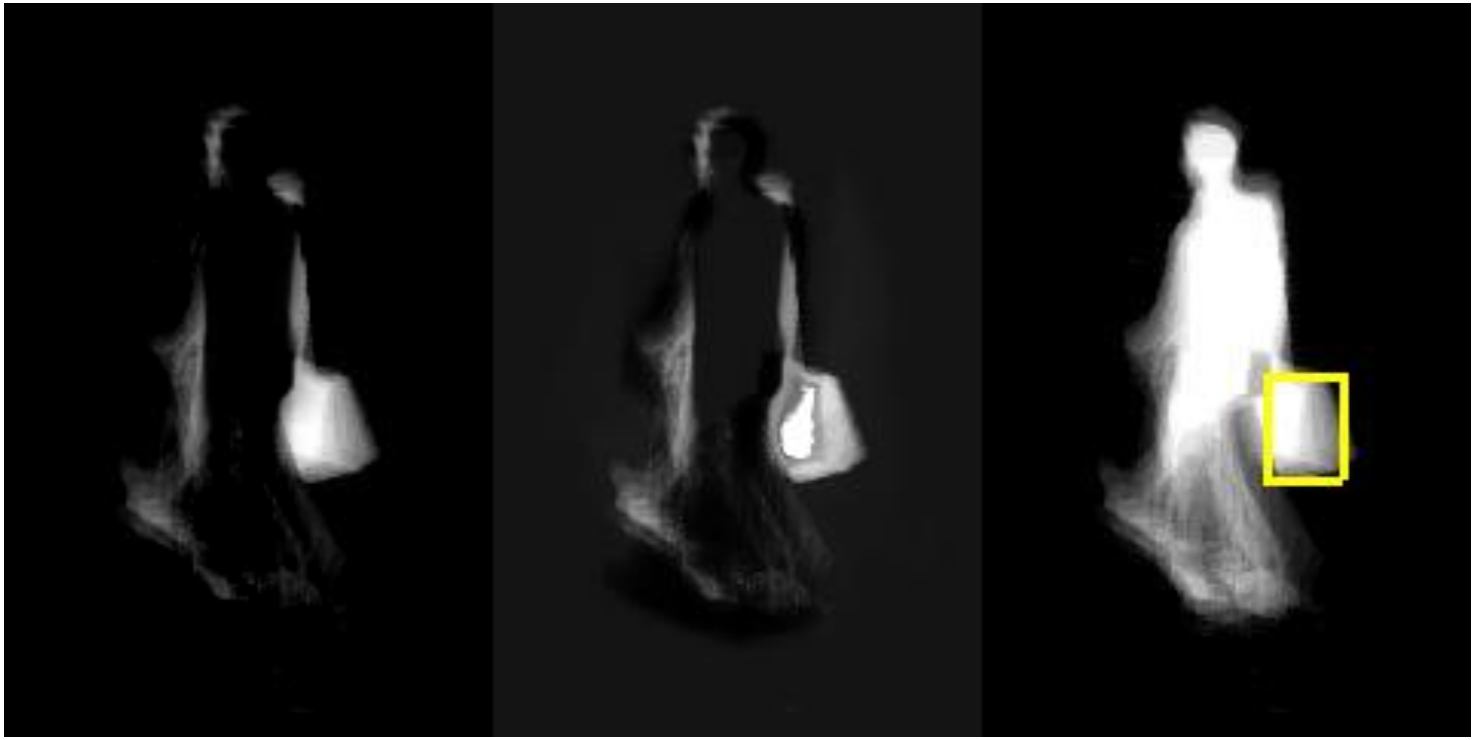
Our Method (Damen and Hogg, ECCV 08)



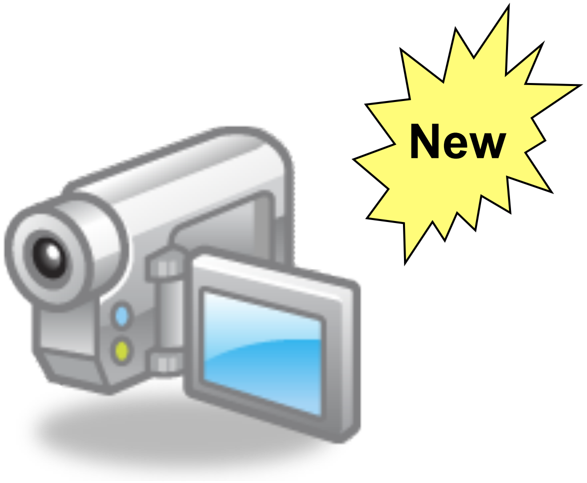
Another Example

Another Example

Another Example



Demo



Current and Future Work

- Grammar-based representation of events of hierarchies
- Automated method to solve similar problems

Thank you ☺

Damen, Dima and Hogg, David (Oct 2008). Detecting Carried Objects from Short Video Sequences. European Computer Vision Conference (ECCV 08).

Damen, Dima and Hogg, David (Sept 2007). Associating People Dropping off and Picking up Objects. British Machine Vision Conference (BMVC 07).

Damen, Dima and Hogg, David (July 2007). Bicycle Theft Detection. International Crime Science Conference. (CS2 07).

http://www.comp.leeds.ac.uk/dima