CSE-571
Probabilistic Robotics

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Applications of
Conditional Random Fields

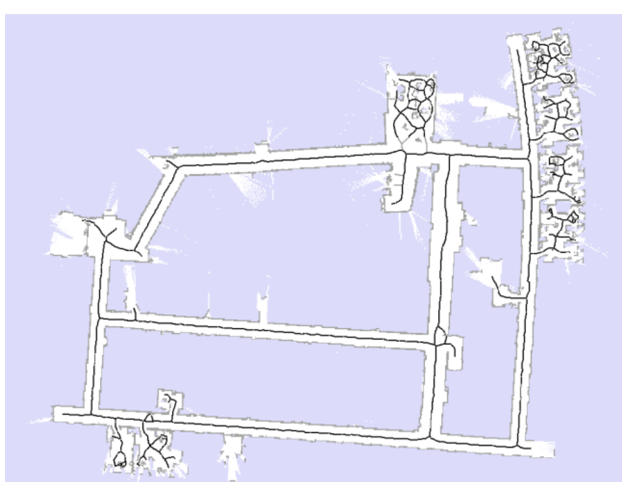
Place Labeling
Line Labeling
Scan Labeling
GPS Trace Analysis

APPLICATIONS OF CRFS

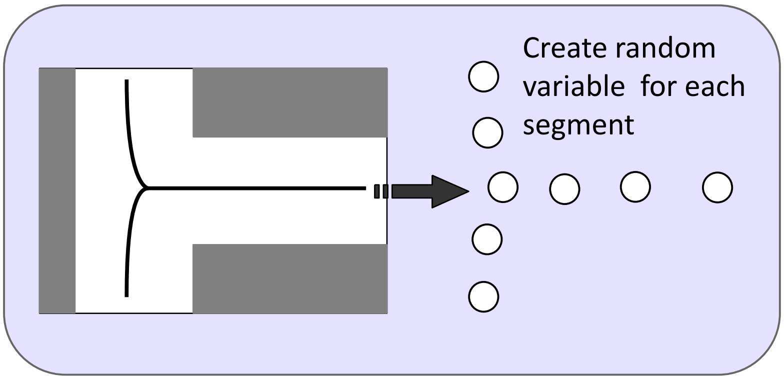
Voronoi Random Fields

- Local approach does not take neighborhood between locations into account
- Voronoi Random Fields
  - Represent free space by Voronoi graph
  - Use Conditional Random Field to jointly label points on the graph

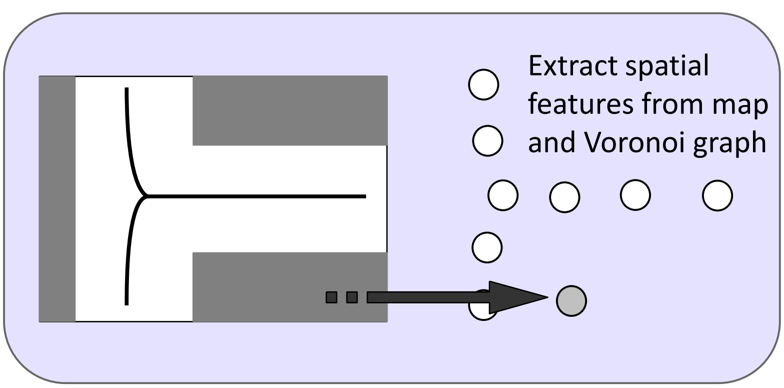
Voronoi Graph



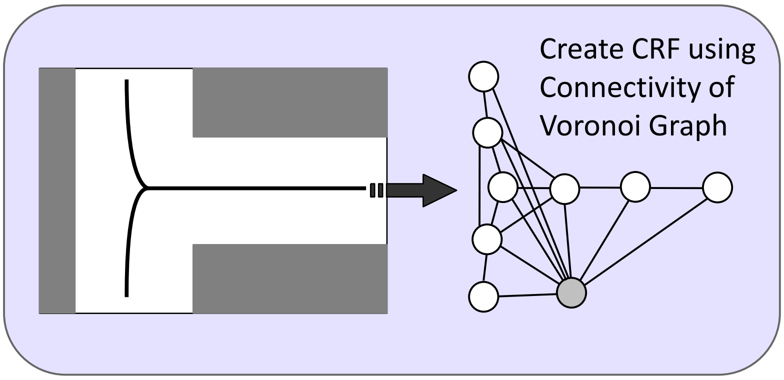
Voronoi to VRF



Voronoi to VRF

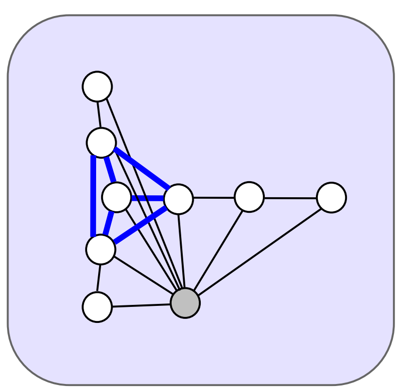


Voronoi to VRF



Multi-Neighbor Cliques

- Distinguish junctions from clutter in rooms

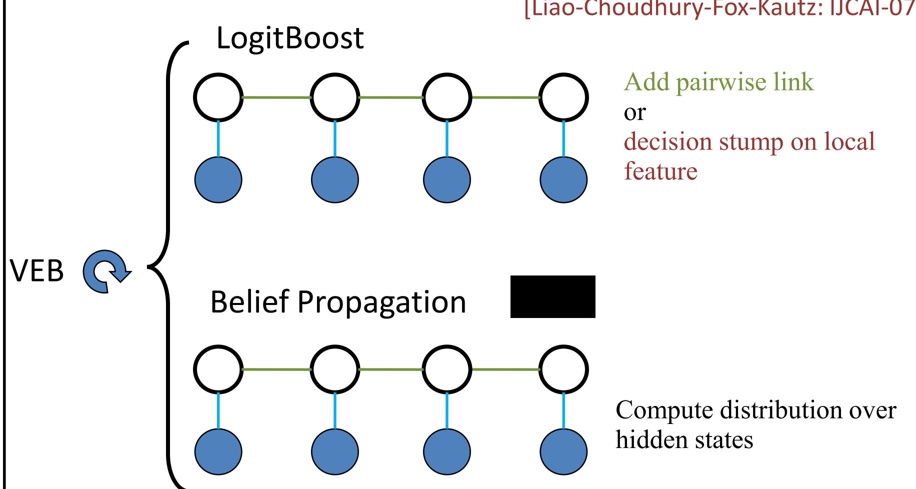


Handling Continuous Features

- Log-linearity for continuous feature value corresponds to Gaussian likelihood
- Not flexible enough
- Incorporate boosted features into CRF

Learning via Virtual Evidence Boosting

[Liao-Choudhury-Fox-Kautz: IJCAI-07]



Evaluation: Accuracy

- Leave-one-out cross validation on hand labeled maps of four different environments
- Learning + evaluation time: ~15min

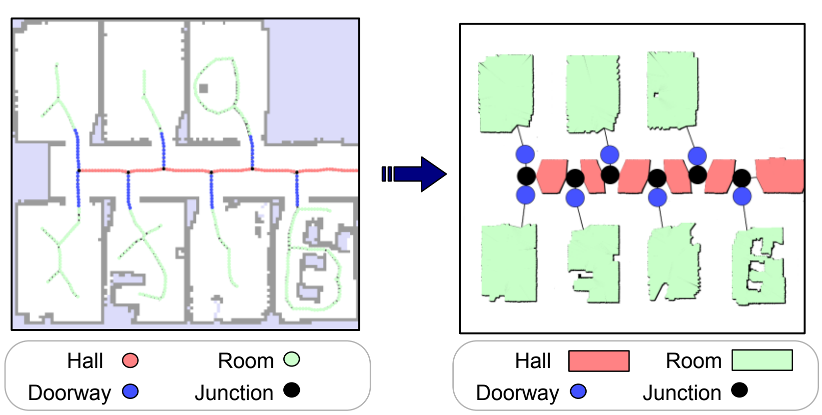
	Accuracy(%)				
	A	B	C	D	**Avg.**
Baseline	87.0	90.8	82.0	81.1	85.2
VRF	93.6	93.3	91.5	86.4	91.2

- Baseline: AdaBoost classification
- VRF: CRF classification with AdaBoost features

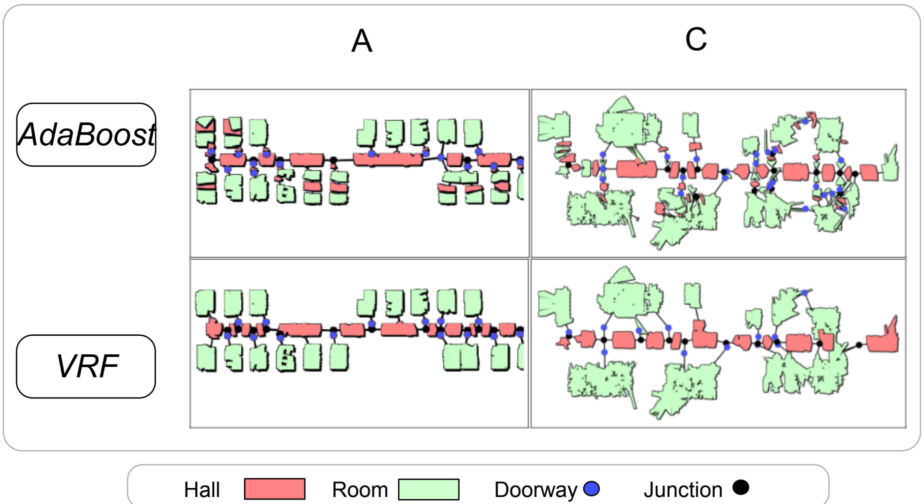
Labeled Voronoi Graph to Metric-Topological Map

Labeled Voronoi Graph

Metric-topological map



Visual Results



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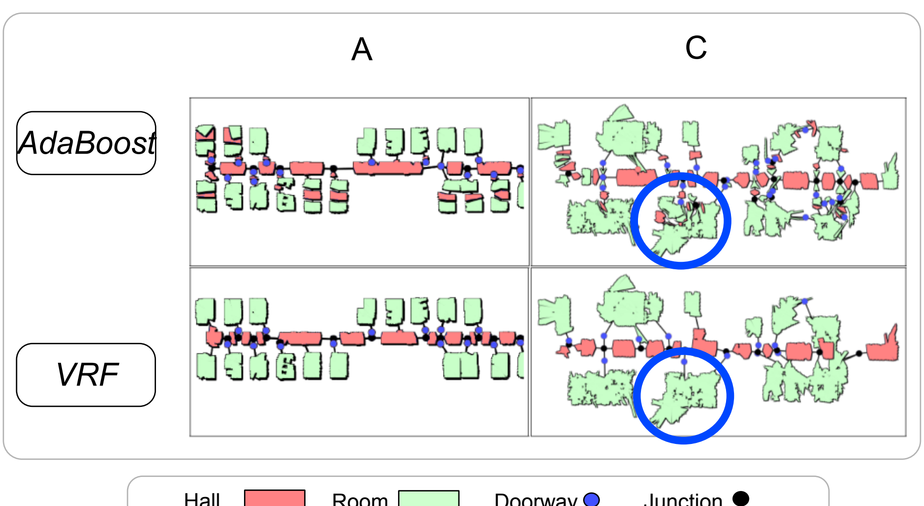


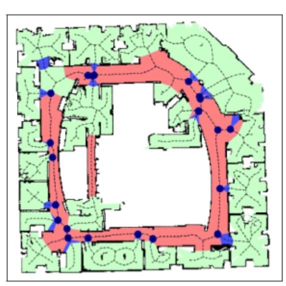
Evaluation: Topological Edit Distance

- Topological Edit Distance Ratio (TED)
  - Shortest paths between 100 pairs of pointss
  - Labels on topological nodes along path as string
  - Ratio of edit distance to path length, smaller numbers are better

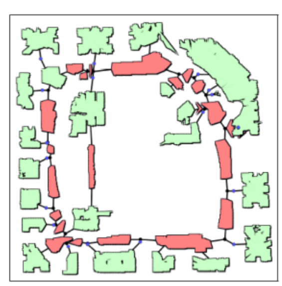
	Topological Edt Distance				
	A	B	C	D	**Avg.**
Baseline	79.4	60.5	76.6	62.6	69.8
VRF	18.2	22.1	23.7	25.7	22.4

Intel Research Lab

Occupancy map

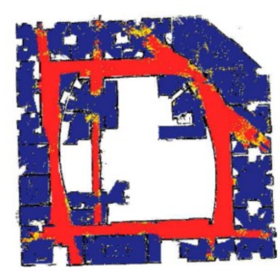


Spatial Labeling



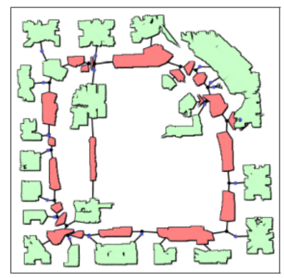
Topological Representation

Comparison to Previous Work



Local Approach

Spatial Labeling



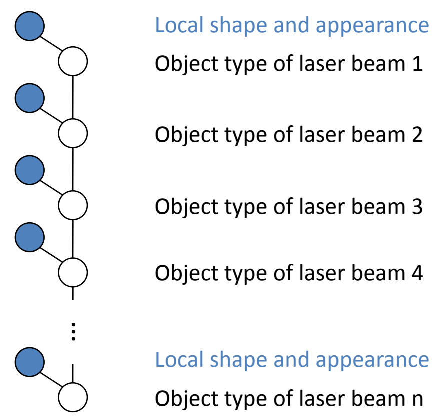
Topological Representation

Target Scenario

[Douillard-Fox-Ramos: IROS-07, ISRR-07]

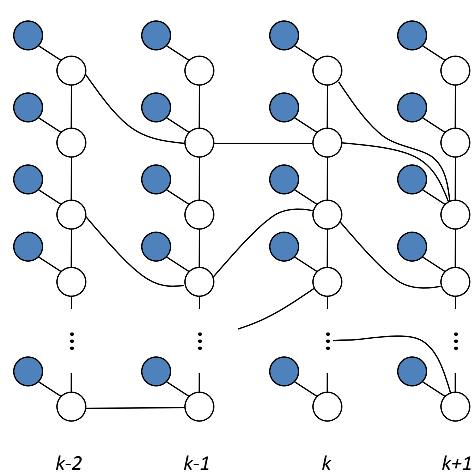
Laser Scan Labeling

- Convert laser scan into CRF.
- Hidden states range over object types.
- Features:
  - Local shape of laser scan
  - Visual appearance around projected laser point (~7,000 continuous values)
- VEB for feature induction and learning.
- Labeling via MAP inference.



Temporal Integration

- Taking past and future scans into account can improve labeling accuracy.
- Match consecutive laser scans using ICP.
- Associated laser points are connected in CRF.
- Can perform online filtering or offline smoothing via BP.



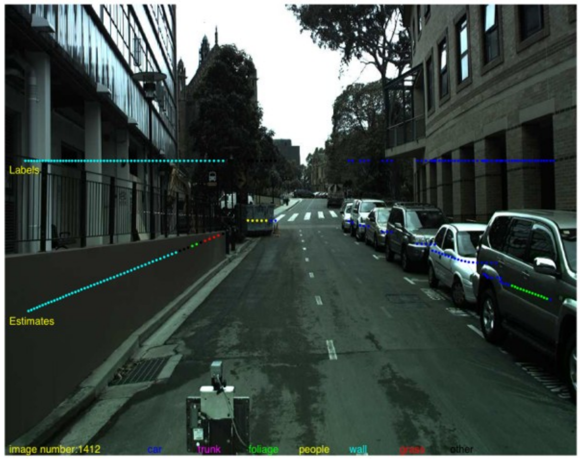
Results

Classifier	Logitboost	CRF	CRF
Time slices	1	1	+-10
Accuracy [%]	55.3	59.0	60.7
Edit distance	5.9	2.6	0.9

- Ten-fold cross-validation on 100 images
- Training on 90 images: 3 hours
- Testing: 6 seconds per image (not optimized)
- Semi-supervised learning helps

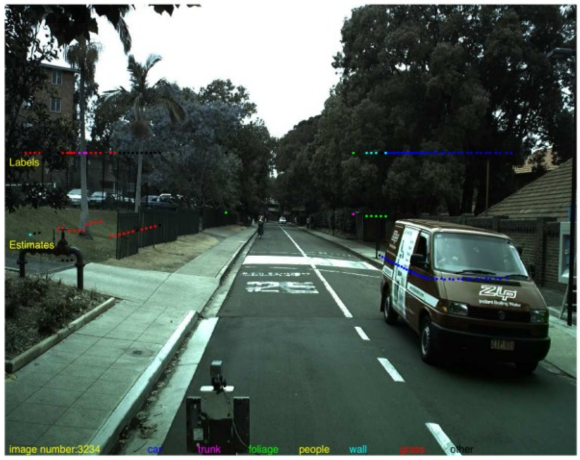
Example Labeling

Example Labeling



Example Labeling

Example Labelings



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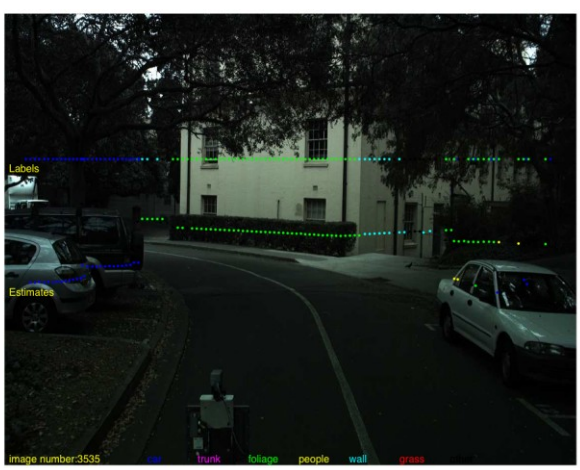

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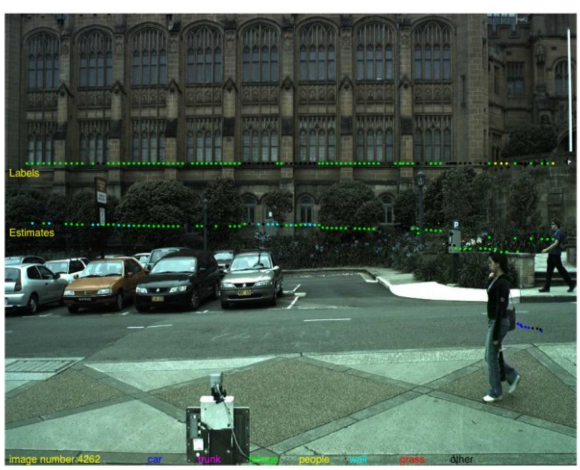
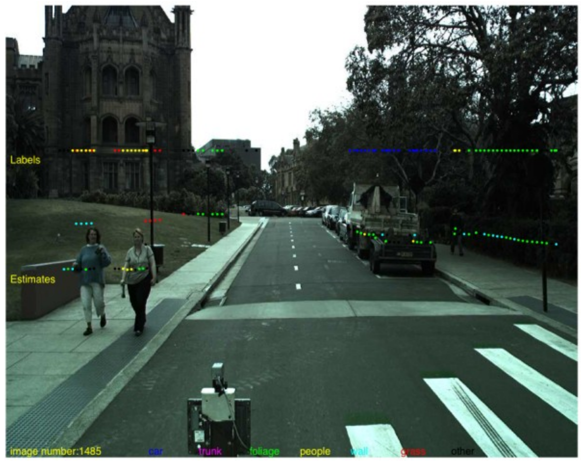


Example Labelings



Place Detection and Labeling

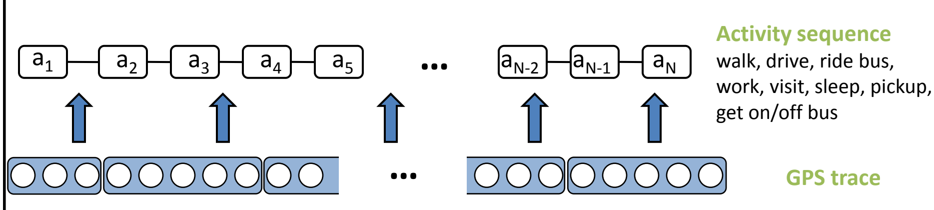
[Liao-Fox-Kautz: NIPS-05,IJCAI-05,IJRR-07]

- Use spatial and temporal information to label locations / activities such as
  - Home, Work, Friend, Other
  - Visit friend, get on / off bus, sleep, work
  - Walk, drive car, ride bus

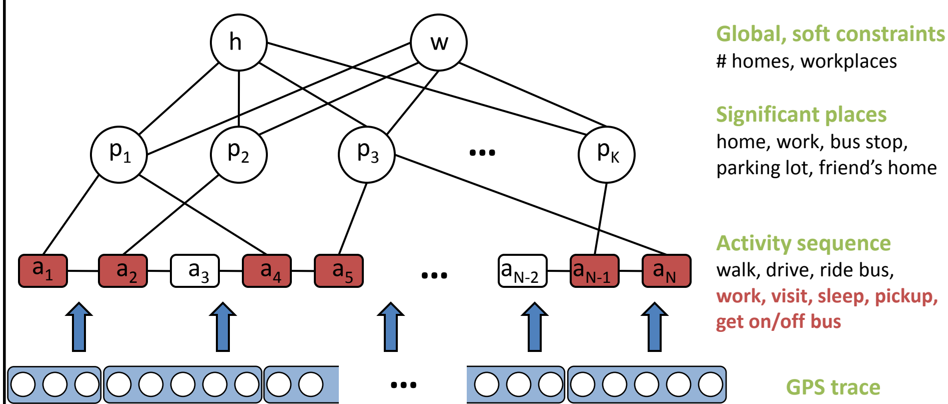
Features

- Temporal pattern: duration, time of day, *etc*.
- Geographic evidence: is there a restaurant / store / bus stop nearby?
- Transition relation: adjacent activities
- Spatial feature: relation between place and activity
- Summation constraint: number of homes, number of workplaces

Hierarchical CRF Model



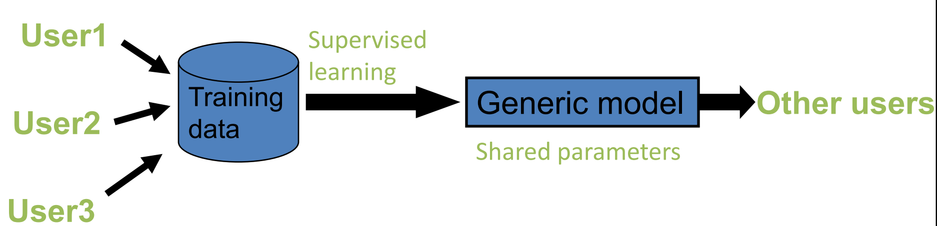
Hierarchical CRF Model



- Two weeks data (> 50,000 gps points)
- Inference: loopy BP (10 minutes); Learning: Pseudo-likelihood (3 minutes)

Learning Generic Model

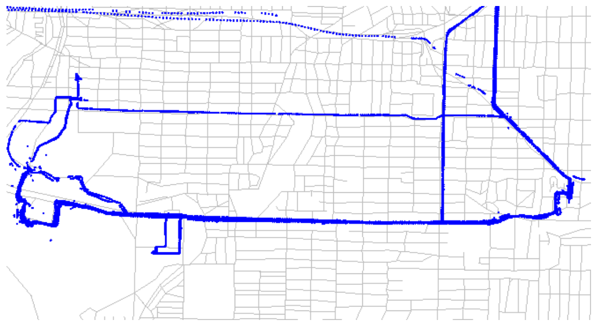
- Generalize from people with labeled data to others without labeled data



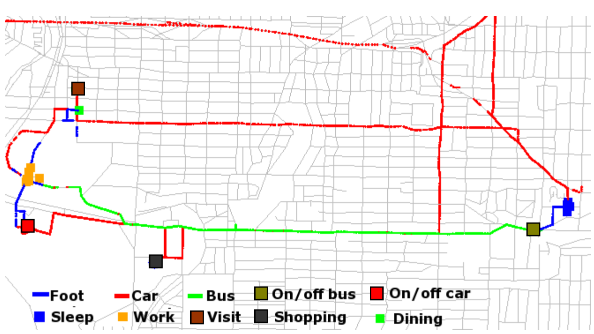
- Relational Markov Networks to specify CRFs and parameter sharing via templates

[Taskar-Abbeel-Koller: UAI-02]

Example



Example



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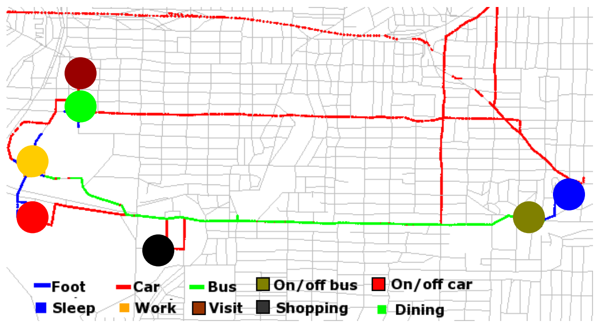

Accuracy / Confusion Matrix

Truth	Inferred labels				
	Work	Home	Friend	Parking	Other
Work	5	0	0	0	0
Home	0	4	0	0	0
Friend	0	0	3	0	2
Parking	0	0	0	8	0
Other	0	0	0	0	28

Cross-validation using data from 4 persons

Summary of a Day

Time	Activity and transportation
8:15am - 8:34am	Drive from home 1 to parking lot 2, walk to workplace 1;
8:34am - 5:44pm	Work at workplace 1;
5:44pm - 6:54pm	Walk from workplace 1 to parking lot 2, drive to friend's place 3;
6:54pm - 6:56pm	Pick up/drop off at friend 3's place;
6:56pm - 7:15pm	Drive from friend 3's place to other place 5;
9:01pm - 9:20pm	Drive from other place 5 to friend 3's place;
9:20pm - 9:21pm	Pick up/drop off at friend 3's place;
9:21pm - 9:50pm	Drive from friend 3's place to home 1;
9:50pm - 8:22am	Sleep at home 1.

Conclusions

- Graphical models provide powerful and flexible framework for learning and reasoning about complex relationships
- Object and place recognition as posterior and MAP estimation
- Conditional Random Fields
  - Can handle high-dimensional features (especially VEB)
  - No need to worry about dependencies