Object-based World Modeling with Dependent Dirichlet Process Mixtures
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Spatial Representation on a Mobile-Manipulation Robot

- Understand environment that robot is operating in:
  - Estimate the state of the world
    - For mobile manipulation, need knowledge of:
      - Free/occupied physical space (for motion)
      - Objects and their attributes (for manipulation)

Semantic World Modeling from Partial Views

- Represent objects in terms of semantic attributes
- Black-box object detector outputs types and poses of objects
- Partial view, occlusion, noise leads to inaccurate detections
- Solution: Aggregate multiple views, seek consistent explanation
  - A single hypothesis is depicted below right, with thick ellipses; ellipse centered at location, color represents type, size reflects uncertainty

Example Scenes and Object Detections

Good:

Bad:

Occlusion causes detection errors

Dirichlet Process Mixture (DPMM)

- Objects as clusters in attribute space
- Association of measurements to objects are latent cluster assignments
- Bayesian nonparametric model allows for ‘infinite’ (unbounded) number of clusters
- Batch processing (sampling sweeps) prevents erroneous commitments

Exclusion Constraint

- ≤ 1 measurement per object constraint
- Couples assignments
- Correct handling causes combinatorial complexity increase

DPMM-Factored: Find and Fix Constraint Violations

- Most groups of objects are unambiguous – cond. indep. nearly holds
- Intermediate samples can be inspected to identify constraint violations

Dependent Dirichlet Process Mixture (DDPMM)

- Incorporate temporal dynamics by introducing dependence across time
- Based on Lin et al. (2010) Poisson-process-based construction
- Allow DP atoms to be added, transitioned, and removed
- Analogy: Objects appearing, changing locations, and disappearing

A Novel Gibbs Sampler Incorporating Future Information

- Previous work used past information only during inference (forward sampling)
- Data association ambiguities may be resolved in the future

Application to Object-based World Modeling

- Include additional domain constraints and information
- Exclusion constraint: See middle column on DPMM
- False negatives:
  - Further discount existence of objects that are frequently not seen in their expected location
  - Sample for sequence of scenes shown in right column
  - Left: No temporal dynamics
  - Right: No domain constraints

Future Directions

- Fast MAP inference: Small-variance asymptotics, with constraints
  - For forward sampling (Campbell et al., 2013), is similar to Kalman filter
  - Gibbs sampling algorithm should give Kalman-smoothing-like algorithm
- Mixture of finite mixtures (MFM): More consistent model?