Bayesian Grasp Planning

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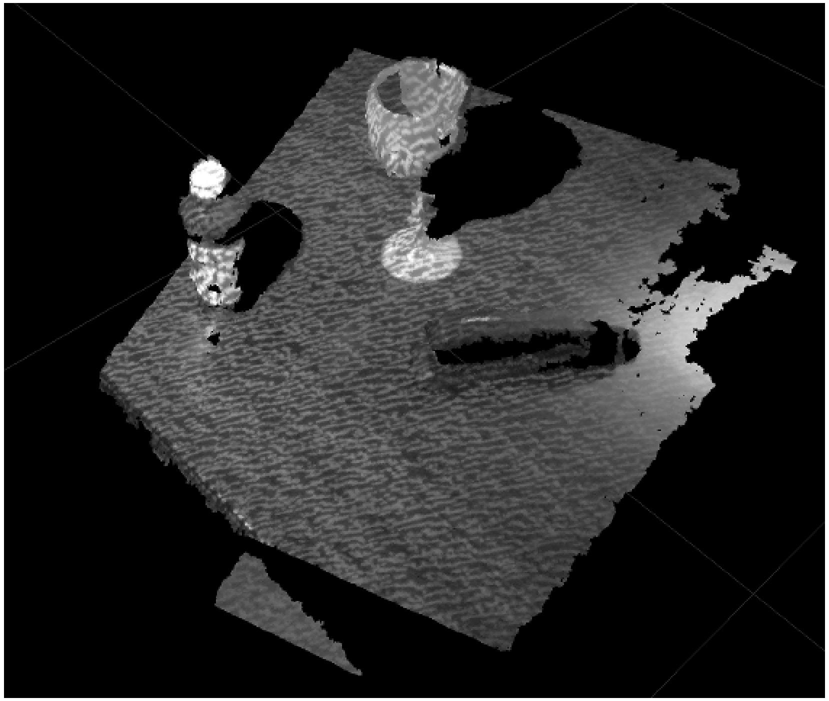
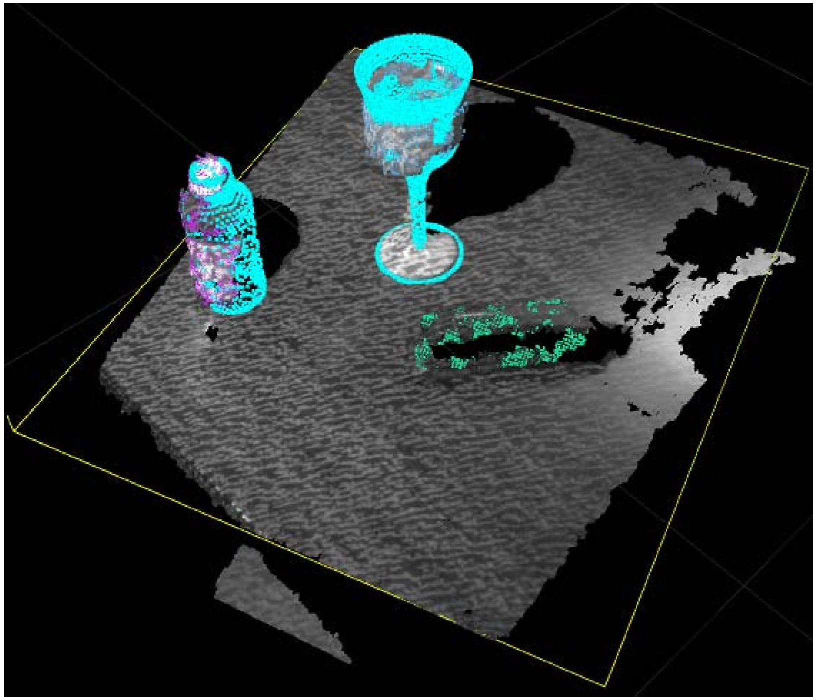
Willow Garage

ICRA Workshop on Mobile Manipulation:
Integrating Perception and Manipulation

The ROS Grasping Pipeline

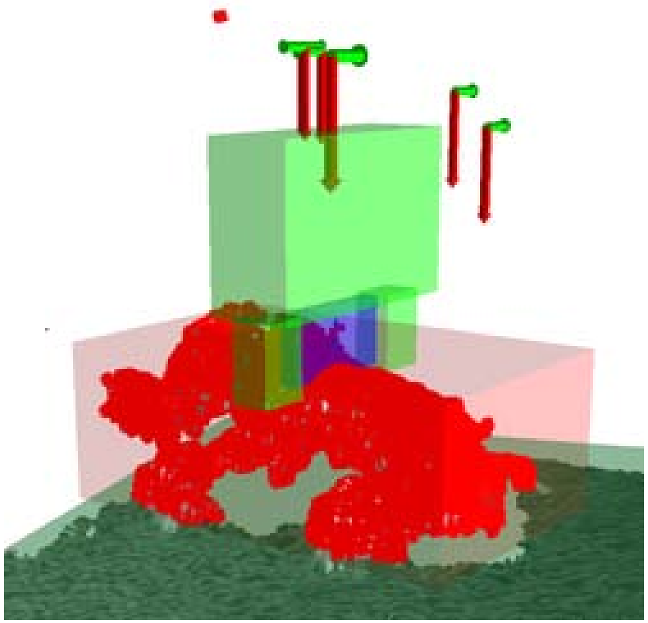
Perception



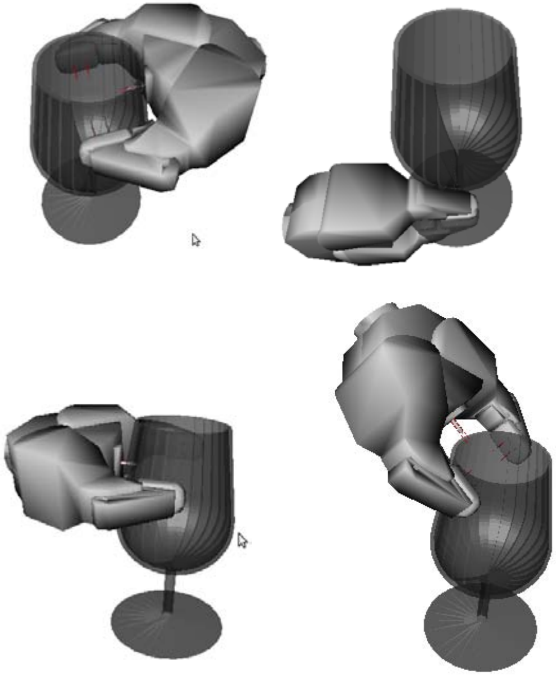


The ROS Grasping Pipeline

Grasp planning



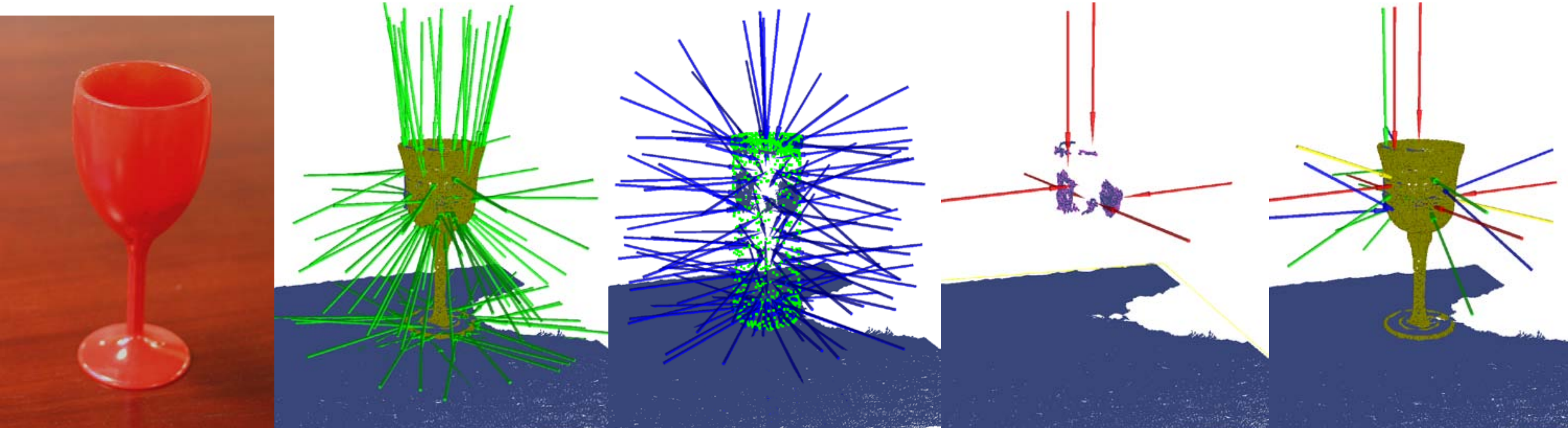
Novel object grasps
[Hsiao *et al.*, IROS 2010]



Known object grasps
precomputed using *GraspIt!*

Bayesian Grasp Planning

- Consider multiple hypotheses for object shape/pose
- Generate pool of grasps planned on all possible object representations
- Evaluate grasps using multiple grasp evaluators
  - Each decides how well a grasp would work on one or more object hypotheses
- Estimate overall probability of success for each grasp



Predicting Grasp Success

$$P(s|E,D) = \sum_{o \in O} P(o|E,D)P(s|E,D,o)$$

Probability of grasp success for a single grasp (g) given the grasp evaluation (E) and object detection (D) results

Assumptions:

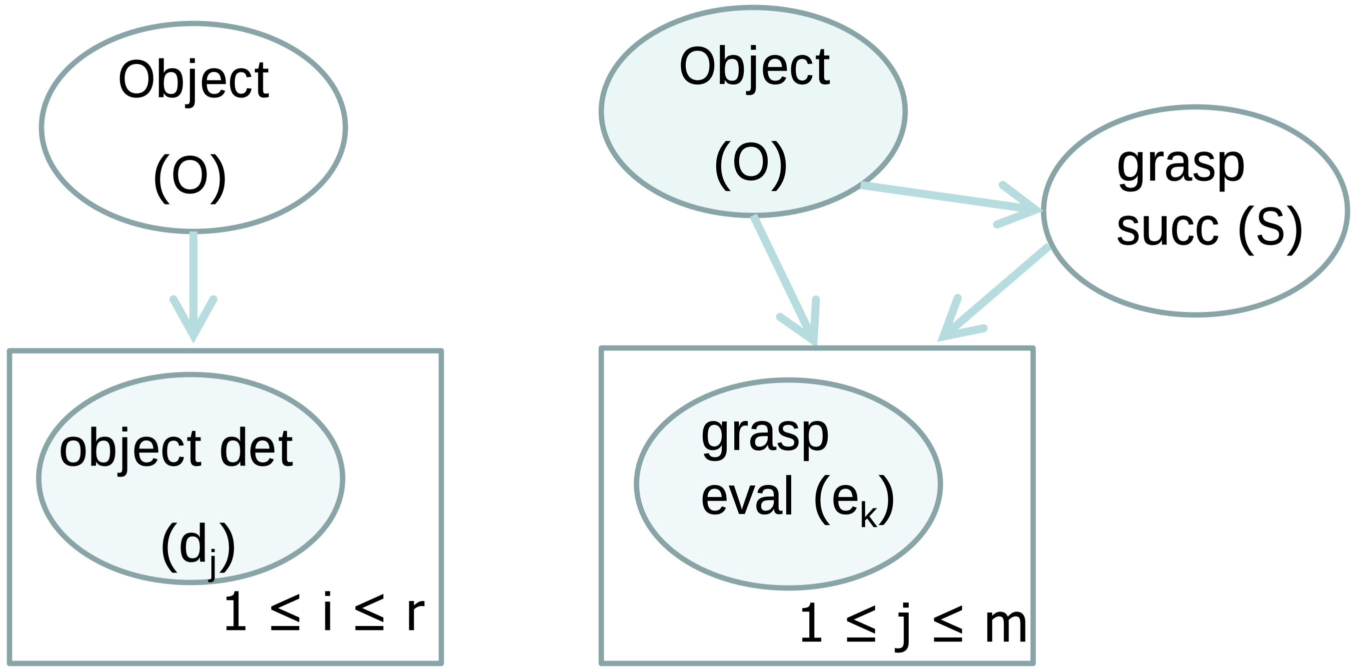
P(s|E,D,o) does not depend on D (because o is given)

P(o|E,D) does not depend on E (which are computed values based on different o)

$$P(s|E,D) = \sum_{o \in O} P(o|D)p(s|E,o)$$

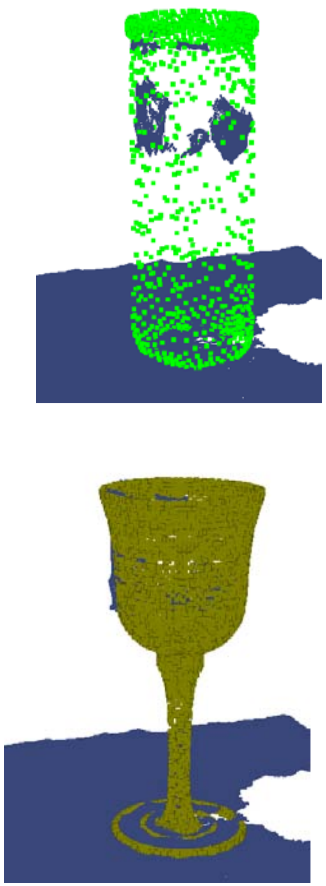
Bayes Net Models

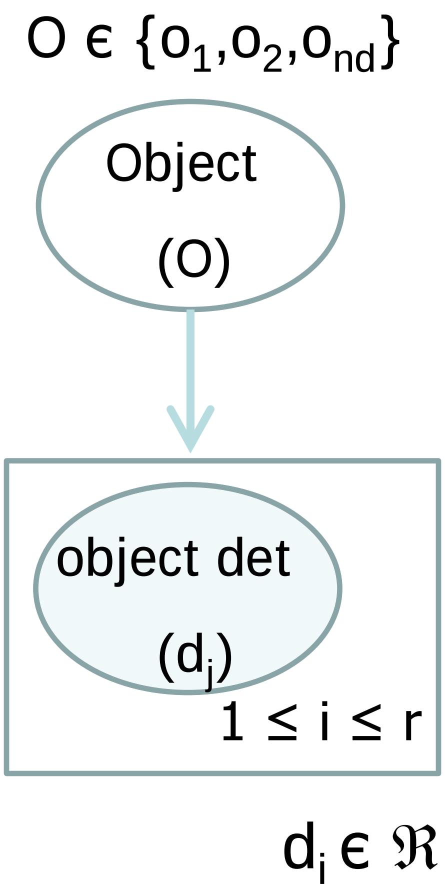
- Split into two pieces because we're assuming P(o|E,D) does not depend on E
- Further assumptions:
  - Object detection results are independent
  - Grasp evaluation results are independent



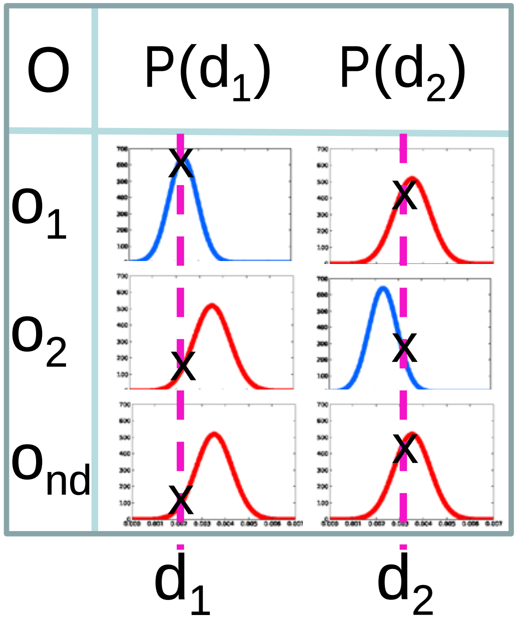
Predicting Object Probabilities

- Naïve Bayes model for object representation probabilities



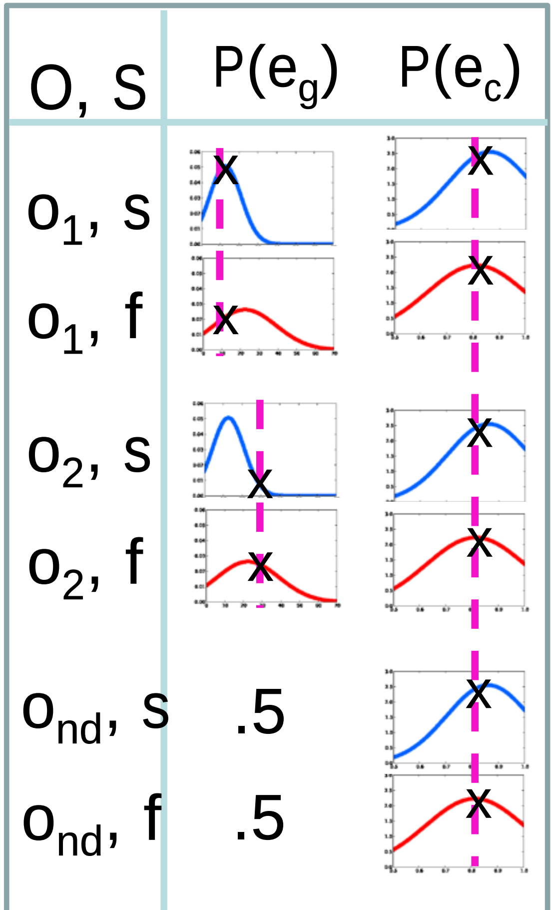


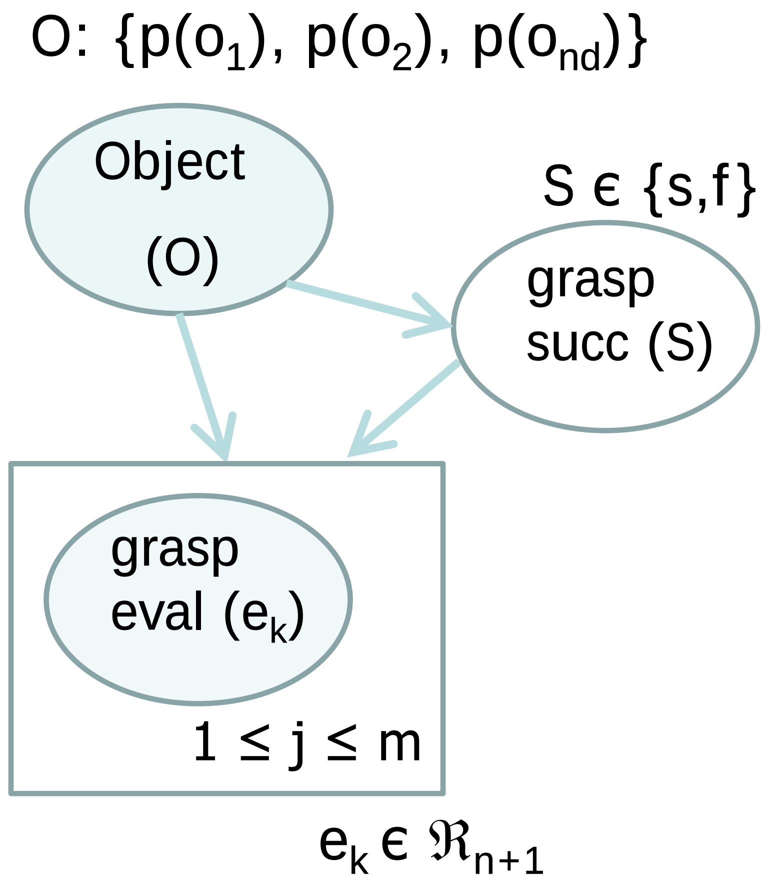
O	$P(o_i)$
o_1	.25
o_2	.25
o_{nd}	.5



Predicting Grasp Success

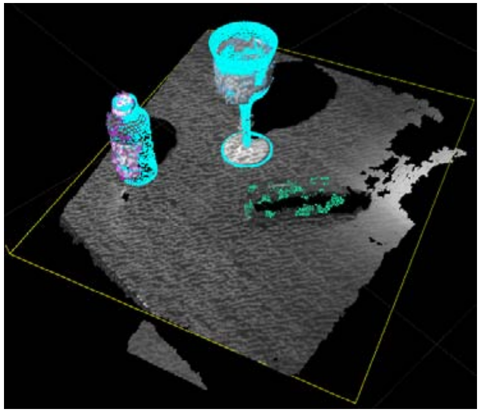
- Bayes Net model for predicting grasp success

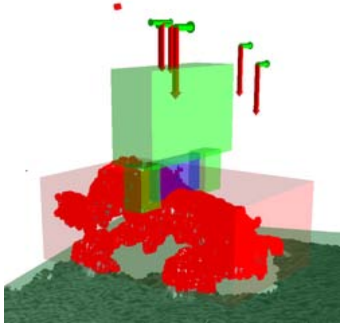


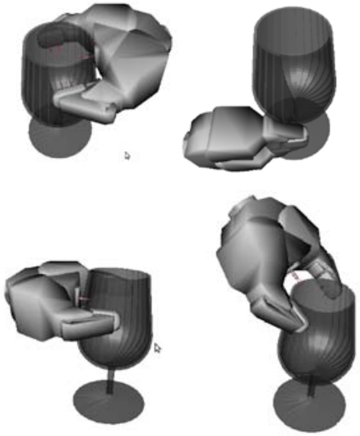


O	P(s)
o_1	.9
o_2	.9
o_{nd}	.9

Current Implementation



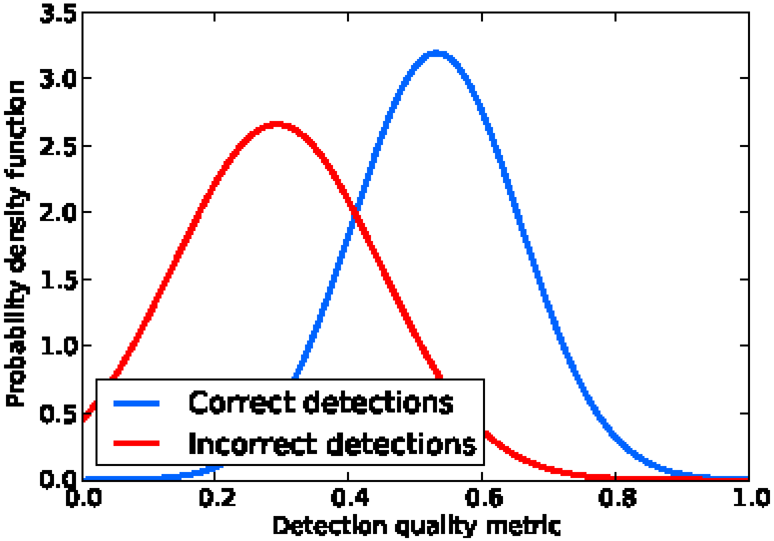




- Object detectors: ICP-like detector for each object in database
- Grasp generators:
  - Precomputed GraspIt! grasps for each detected object
  - Grasps planned by point cluster grasp planner
- Grasp evaluators:
  - GraspIt! grasp testing
  - Point cluster grasp planner evaluator

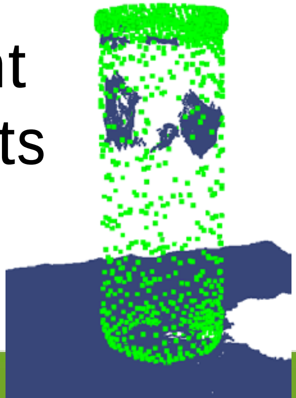
Conditional Distributions

Object detection

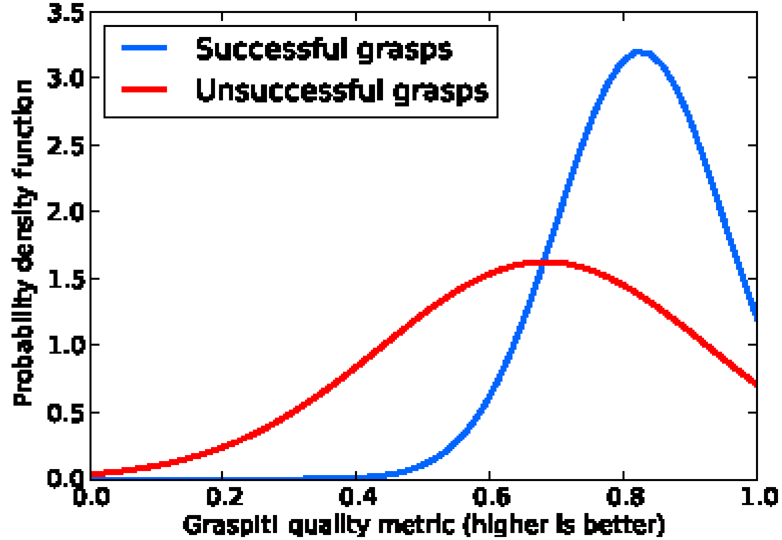


$P(d_j|o_i)$, $P(d_j|\neg o_i)$

Based on 892 point clouds of 44 objects

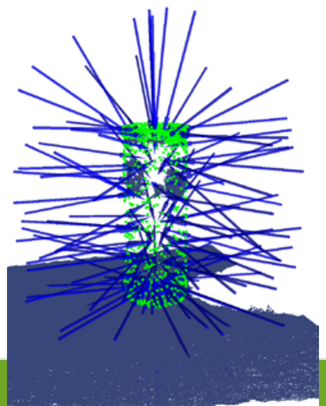


GraspIt! energy metric



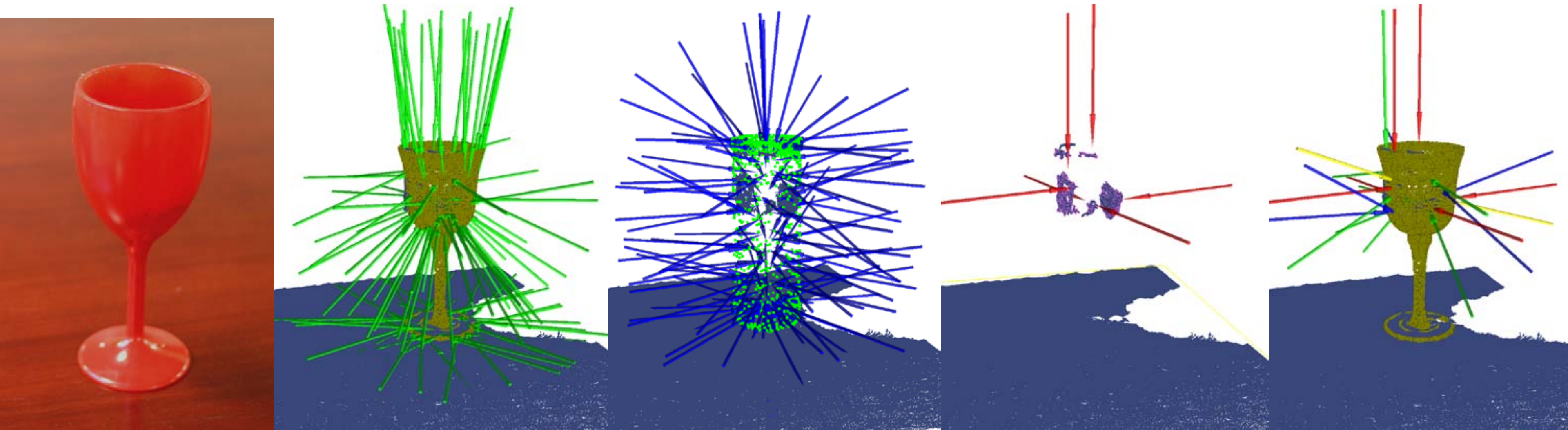
$P(e_k|s, o_i)$, $P(e_k|f, o_i)$

Based on 490 recorded grasps of 30 objects



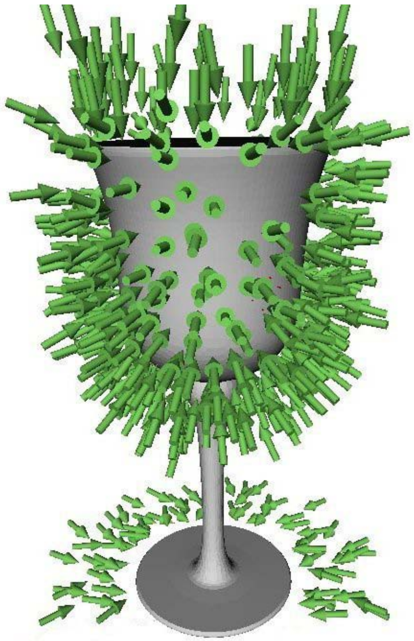
Bayesian Grasp Planner

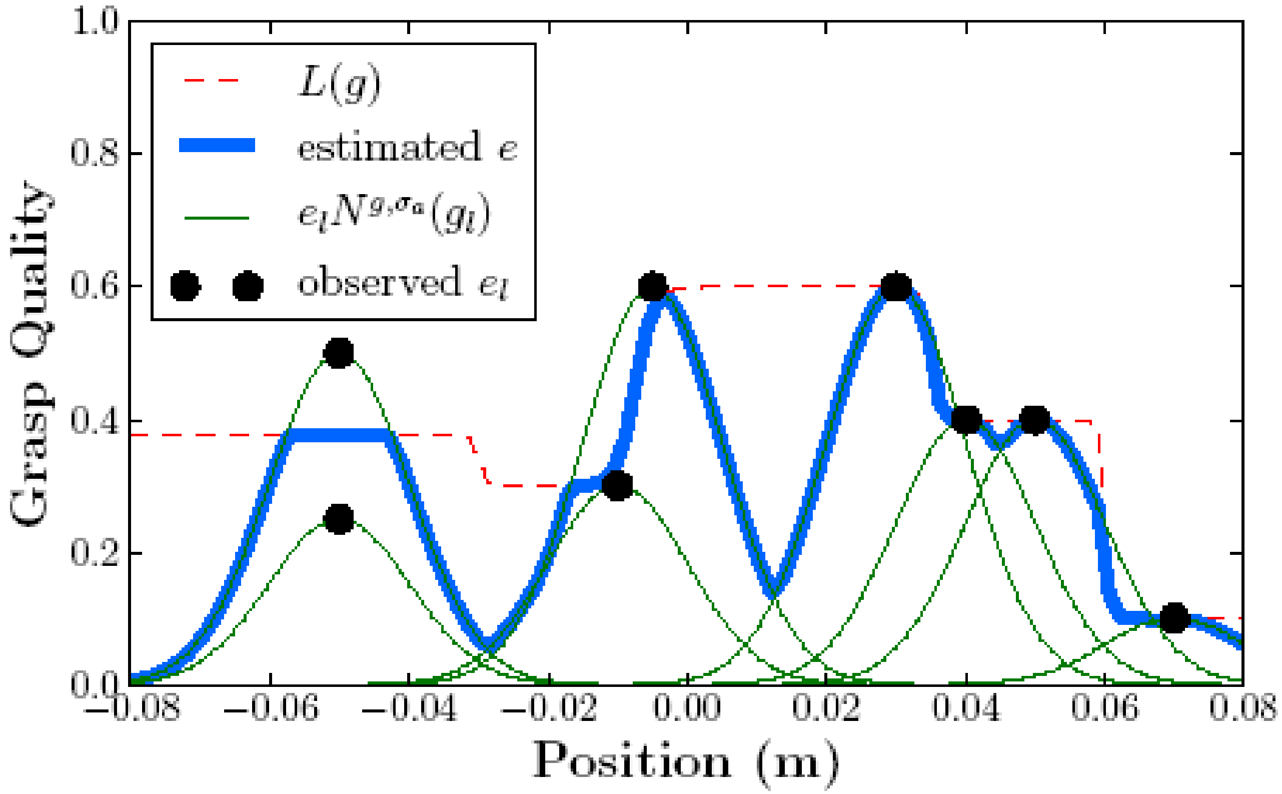
- Object detectors generate list of object representations
- Grasp generators create pool of grasps to evaluate
- Grasp evaluators for each representation say how well each grasp would work on that representation
- Overall success probability estimated for each grasp



Grasp Quality Regression

- Explicit GraspIt! evaluation of arbitrary grasps too slow to evaluate hundreds of grasps
- Precomputed grasp database has dense sampling of good grasps—use regression to estimate grasp quality

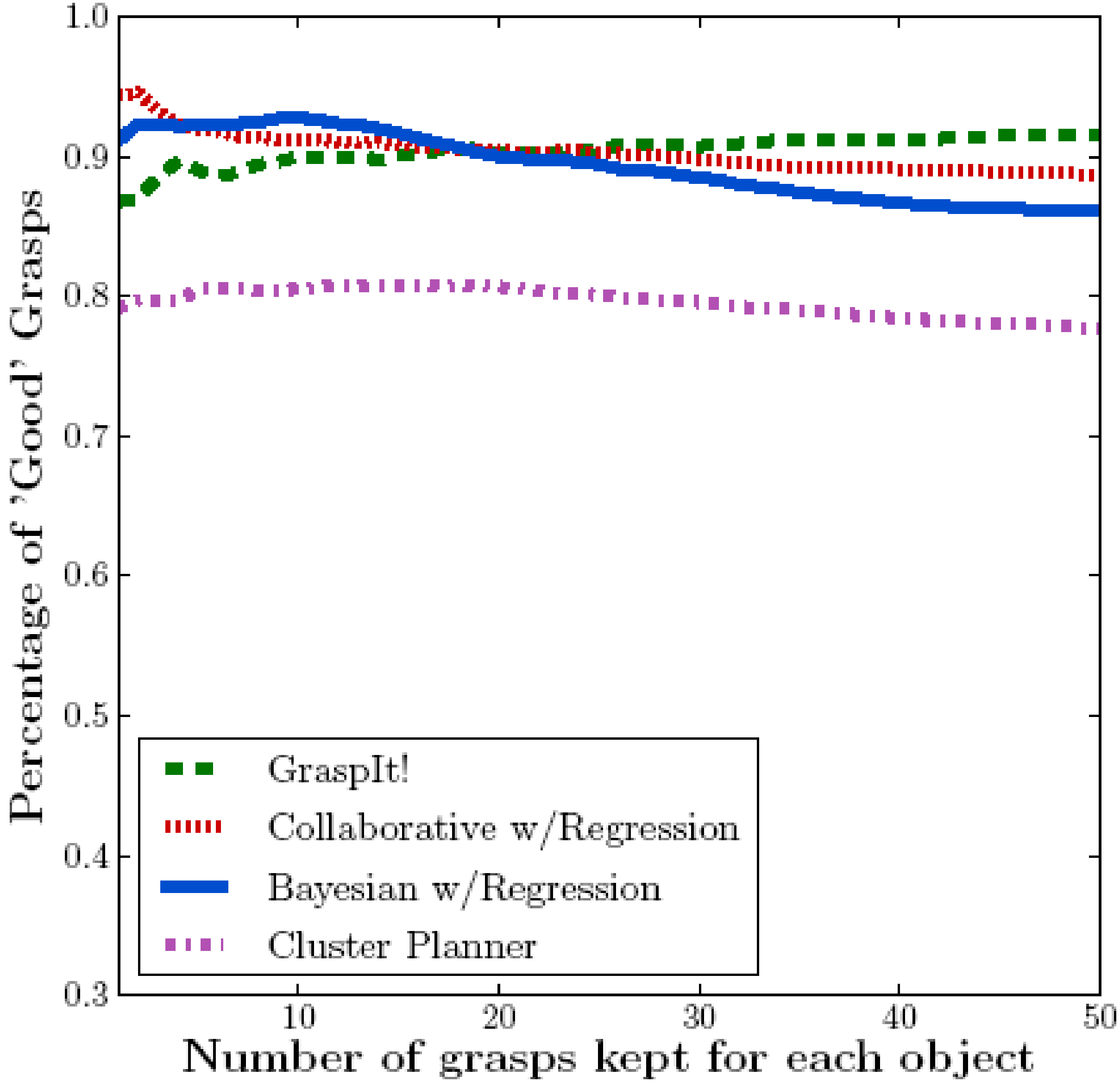




Simulation Results: Database Objects

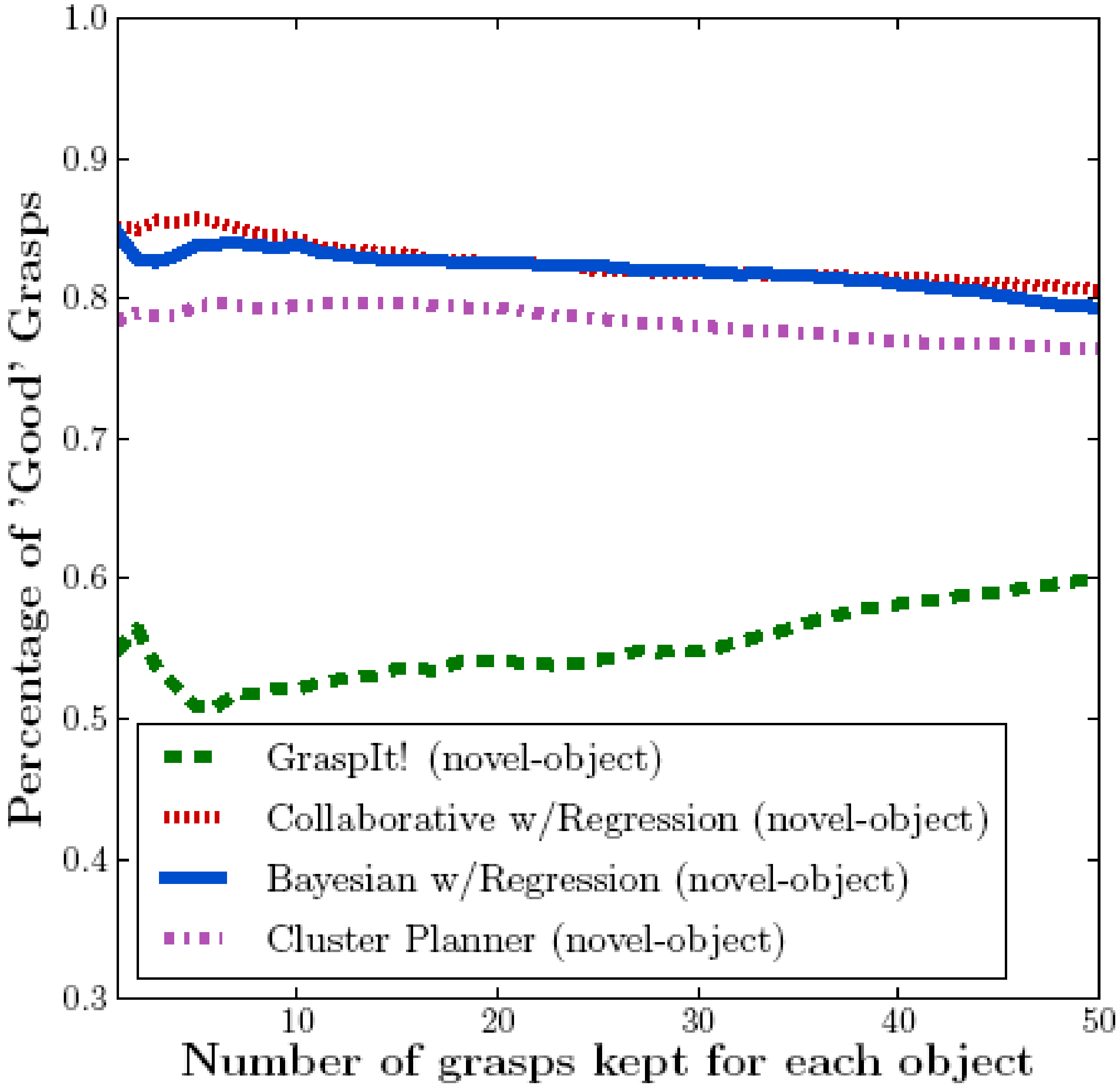
- Generated using 250 real object scans (single-object-on-table)

- Grasps are tested in GraspIt! on the ground-truth object geometry



Simulation Results: Novel Objects

- Generated using the same 250 real object scans
- Object is taken out of the database
- Grasps are tested in GraspIt! on the ground-truth object geometry



PR2 Results

	Collaborative Planner	Naïve Planner
Novel objects	22/25	18/25
Database objects	22/25	21/25

- Single object on table
- Success = lift and move to side without dropping

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Bayesian Grasp Planning Summary

- Deals with uncertainty in object shape/pose
- Combines arbitrary number of object detection, grasp planning, and grasp evaluation algorithms
- Looks for consensus on how to grasp based on multiple representations of the sensor data
- Framework increases robustness to errors in object detection based on incomplete or noisy sensor data