Category-based task specific grasping

**OFFLINE part**
- Generation of task-specific grasps
  - Stability weights
- Optimization
  - \( \arg \max_X P(X) \)
  - "Good" grasp

**ONLINE part**
- Registration of a new object
  - Fitting weights

1. Training stage (in GraspIt! simulator)
   - Training set: objects of the same category ("mugs", "tools" from CGDB)
   - Generate reference grasps per each model in category using Barrett Hand model ("top", "side", "handle")
   - Store stability quality metric (epsilon QM)

2. Registration of a new object
   - Get point cloud of a new object from a single RGB-D image using Kinect sensor
   - Transform training models into point clouds
   - Perform the registration using Point Cloud Library:
     - Extract key points and calculate local descriptors (Fast point Feature Histograms)
     - Apply Iterative Closest Point approach
   - Obtain fitting scores from registration

- Each task-specific grasp is parameterized by 6DOF pose \( X \) and represented by weighted density function (Gaussian or Laplace distributions)
- To find an optimal grasp we maximize the expected probability of grasp \( X \):
  \[
  \arg \max_X P(X) = \sum_i P(\varepsilon_i) P_i(X)
  \]
  - \( P(\varepsilon_i) \) - the probability of the new object to match the training object \( i \)
  - \( P_i(X) \) - the probability of the grasp \( X \) to be stable on the training object \( i \)

- The method outperforms classical most similar model’s grasp approach (“best single”) resulting in more stable grasps
- The method can generalize for similar in shape objects from other categories