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Department of Computing
Imperial College London

Explain What You See:
Argumentation-Based Learning & Local Hierarchical Dirichlet Process

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XAI Seminars

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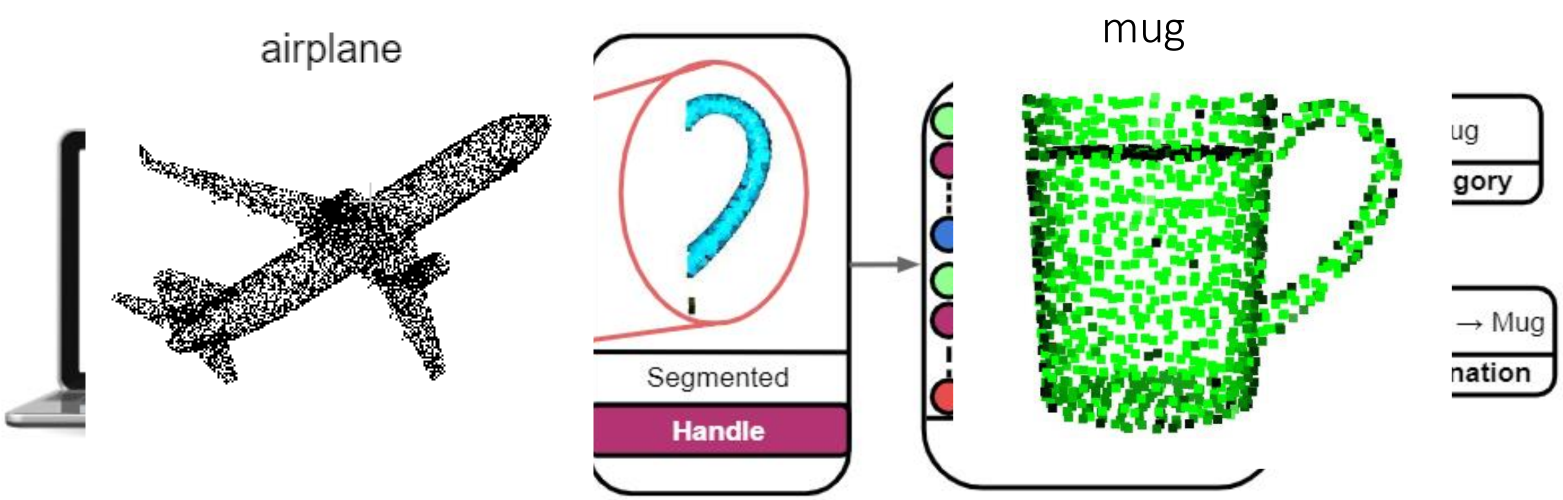
Outline of The Presentation

- Introduction
  - Problem statement
  - 3D Object Category Recognition
  - Clutter and Occlusion
  - 3D Object Parts Segmentation
- Background
  - Argumentation-Based Learning
  - Local-Hierarchical Dirichlet Process
- Explain What You See
  - ABL for 3D Object Category Recognition
  - Making Occlusion Dataset
  - Results
- Conclusion

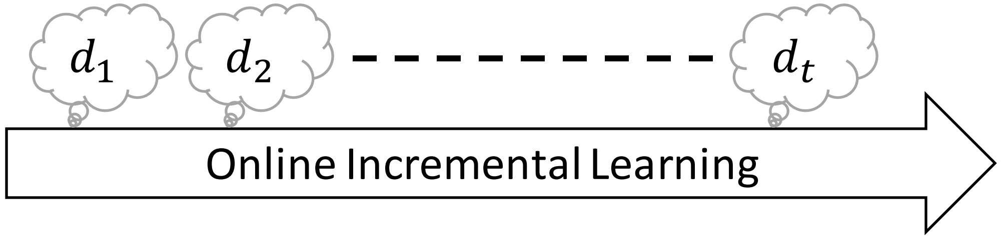
Problem Statement

- **3D object** category recognition
  - **Classifying** a 3D object to a specific **category of objects**
- **Explain** the reasons for classification of each 3D object to a specific category of objects using the information about the **3D object parts**.
  - Explainability with **Argumentation-Based Learning (ABL)**
  - 3D Object Parts Segmentation with **Local Hierarchical Dirichlet Process (Local-HDP)**



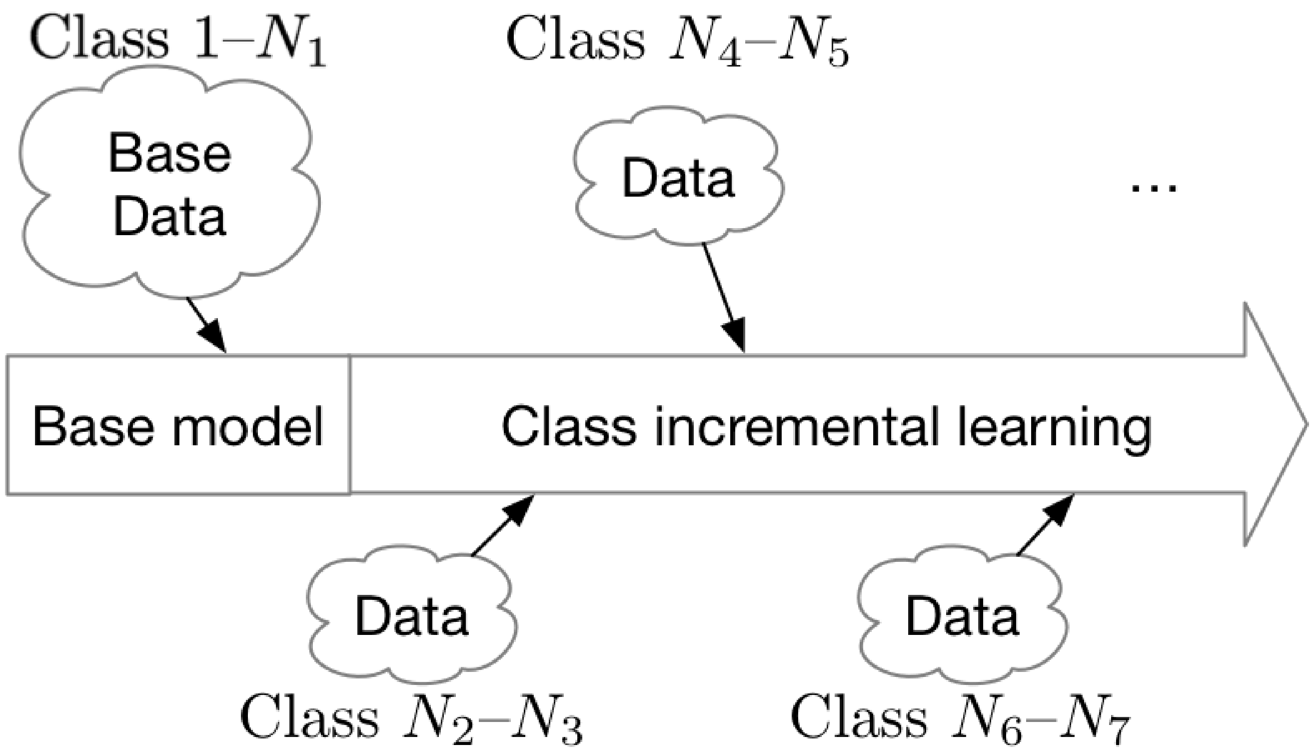
Online Incremental Learning

- A sequence of data enters the model
- The model has to adapt **incrementally** i.e. M_{i+1} is constructed based on M_i without a complete retraining.
- The model should preserve the acquired knowledge
- **Online learning** means that you learn as the data comes in. **Offline** means that you have a static dataset.
- Another wrinkle that can affect **online learning** is that your concepts might change through time.
  - Concept-Shift
  - Catastrophic Forgetting -> In NNs



Lifelong (Open-Ended / Class-Incremental) Learning

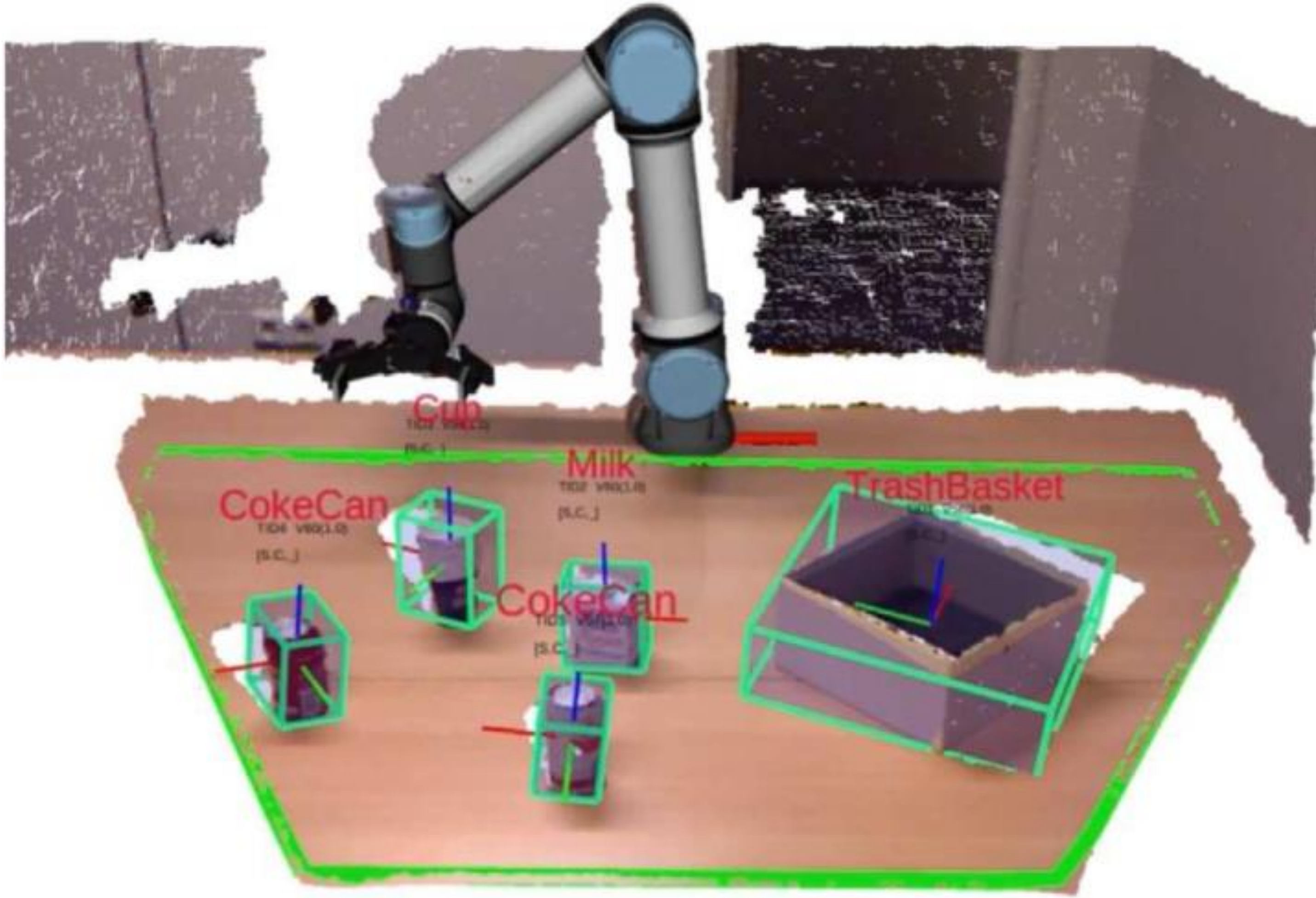
- Supervised Learning
- The number of class labels are not fixed.
- It can grow over time.
- The model should be able to handle learn new classes without a need for complete retraining.
  - Problem in most deep neural networks
  - Also in other methods like probabilistic models



3D Object Category Recognition

- **Input:** The ***point cloud*** of 3D objects
- **Output:** ***Category*** label of the 3D Objects

- **Point Clouds** and **RGBD** images
  - RGB + Depth: (r, g, b, x, y, z)
  - 3D Cameras
    - Kinect is a 3D camera!
    - Along with the RGB values of every pixel, it also gives you the depth values associated with every pixel.
    - It uses structured infrared light to determine depth values.



Real-Time Robotic Applications:

First Robotic Demonstration:

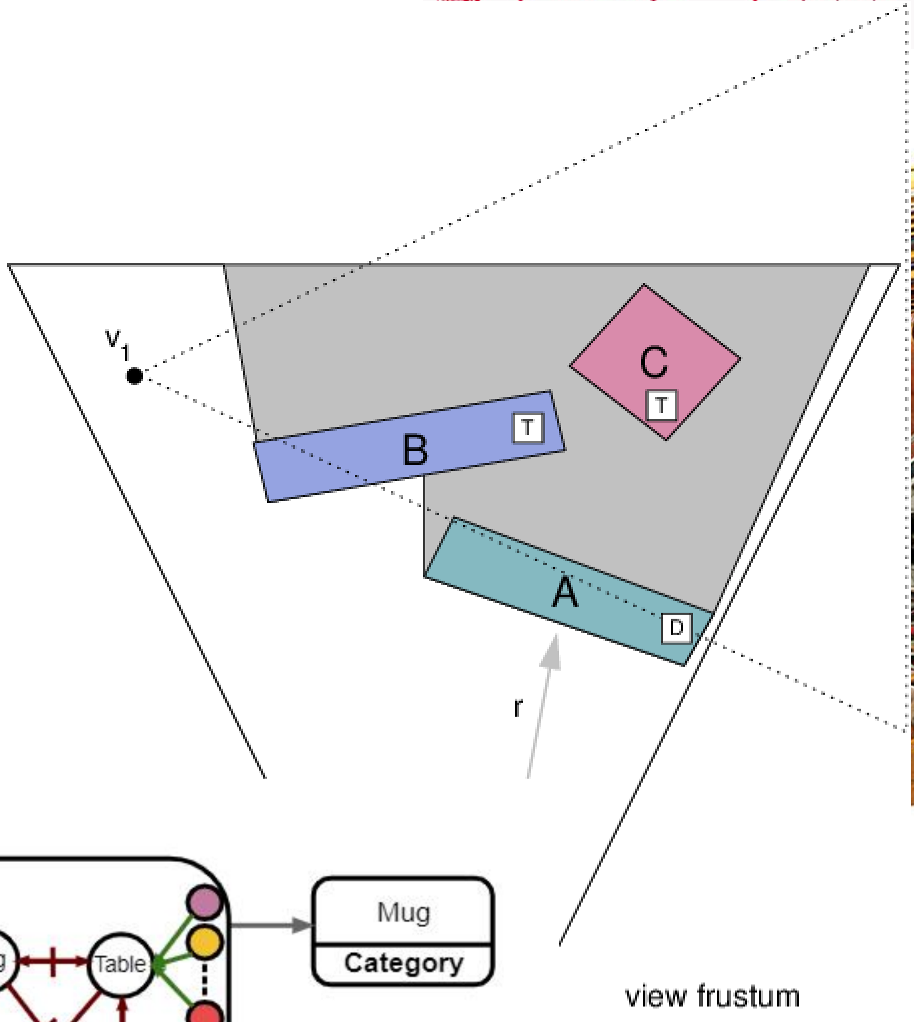
- Goal:
    - Learn Unforeseen Object Categories
    - Manipulate the recognized objects (Clean Table)
- Human-Robot Interaction:
    - User Interface

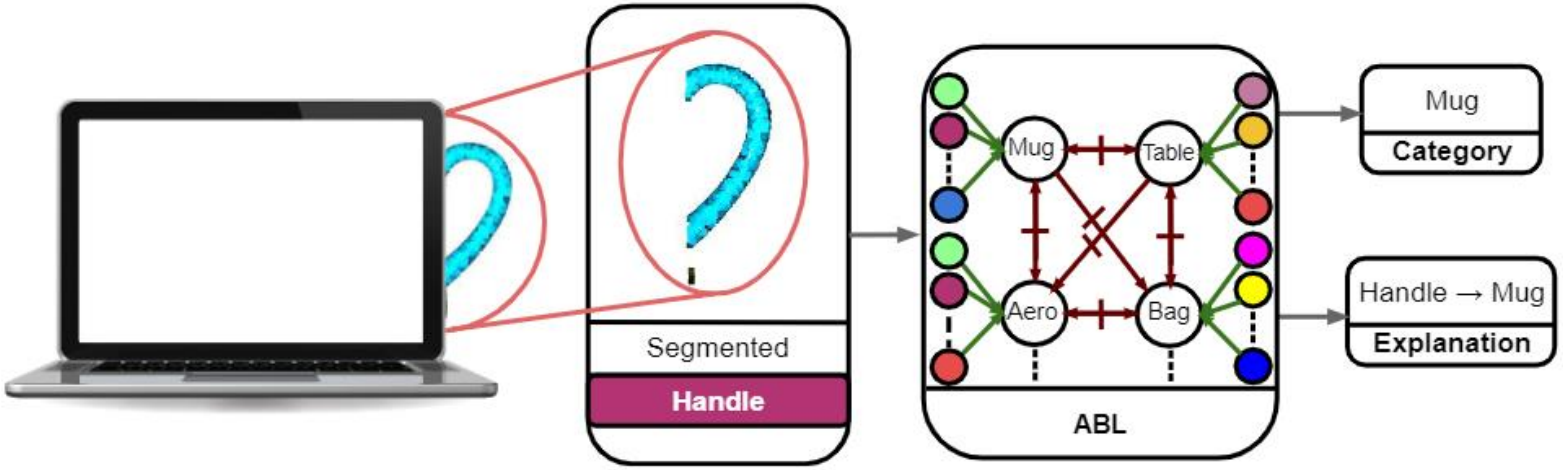
Second Robotic Demonstration:

- Goal:
    - Learn Unforeseen Object Categories
    - Recognize Unforeseen Objects
    - Category Specific Task (Cleaning all the cans)
- Human-Robot Interaction:
    - Voice Command

Clutter and Occlusion

- **Clutter:** a collection of things lying about in an untidy state.
- **Occlusion:** two or more objects cover parts of other objects.





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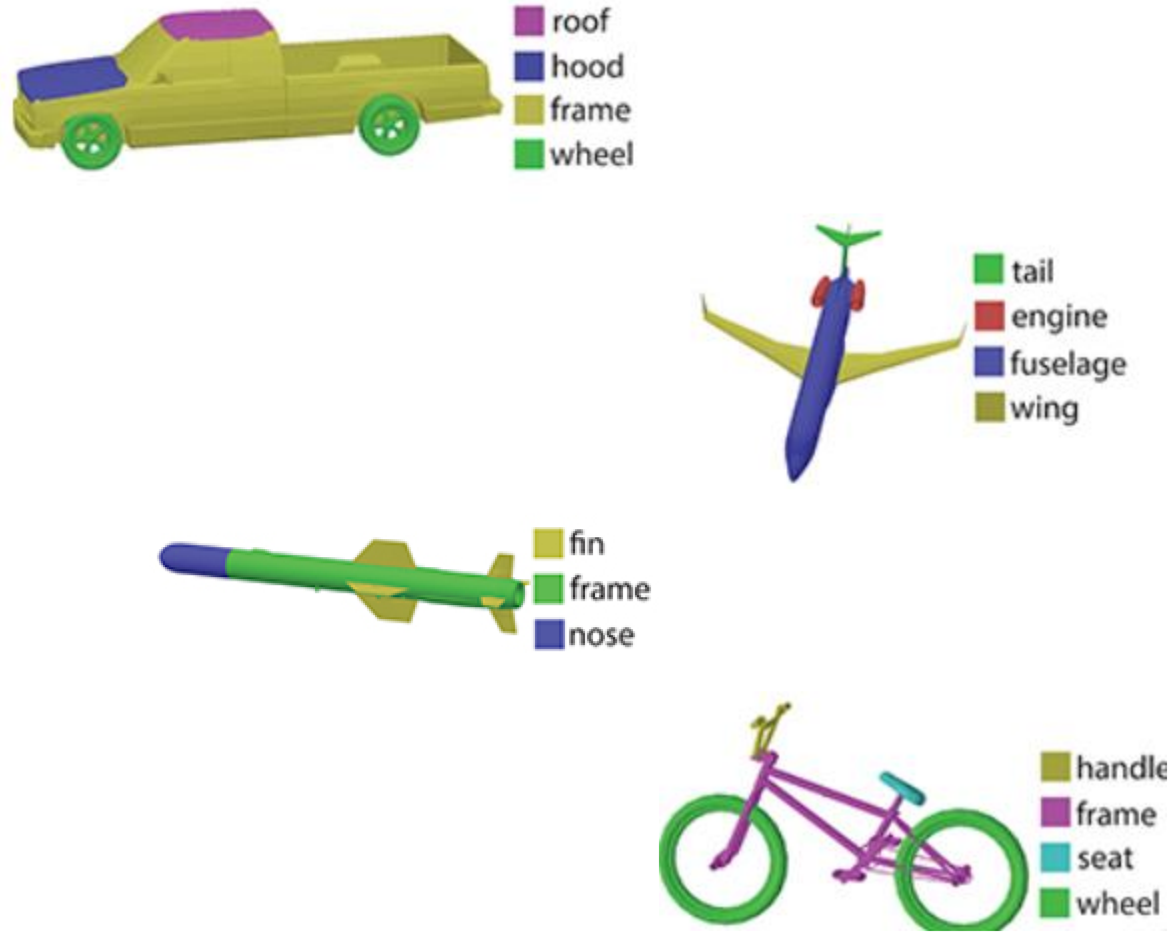
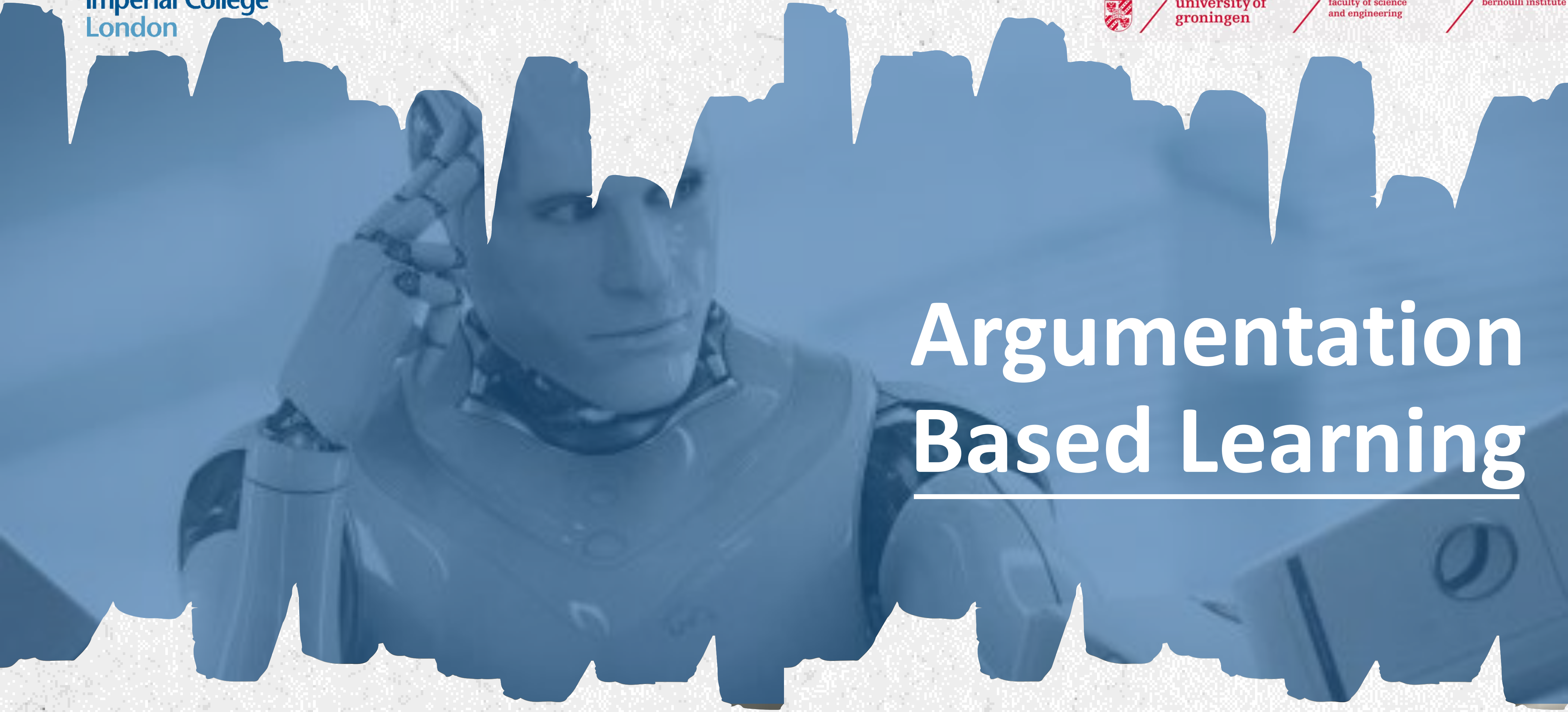
3D Object Parts Segmentation

- **Input:** The ***point cloud*** of 3D objects
- **Output:** *Object **Parts Segments.***

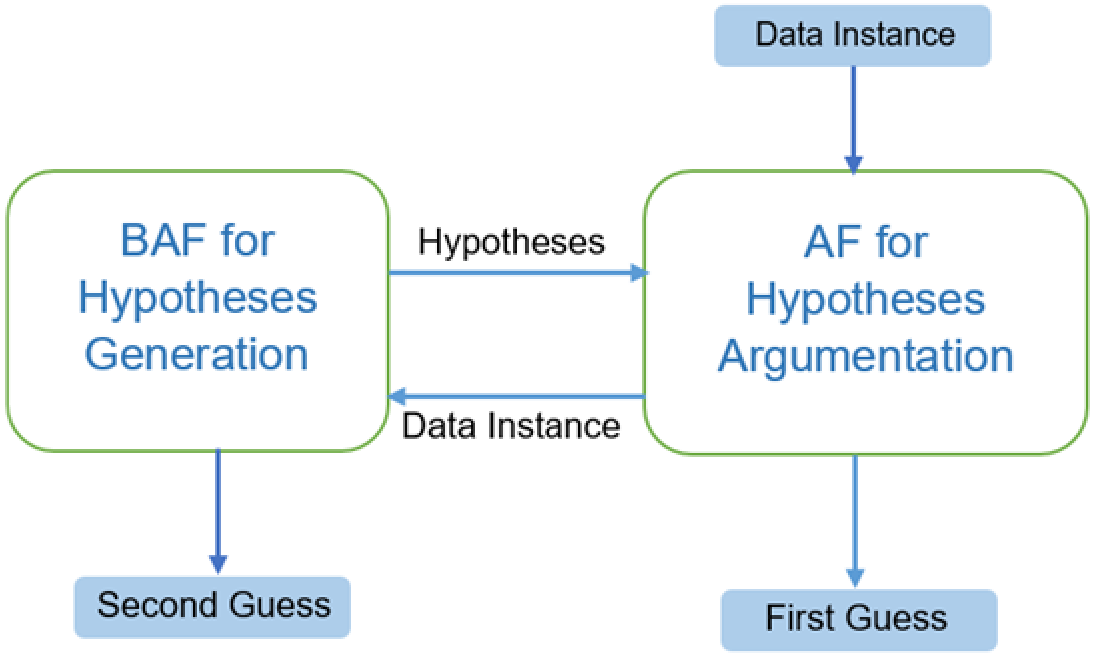




Argumentation Based Learning

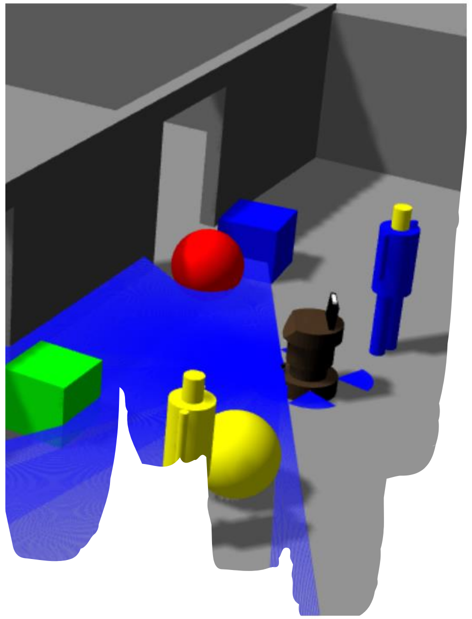
The architecture of Argumentation-based Learning (ABL)

- **BAF Unit (Left):** Weighed Bipolar Argumentation Framework (BAF) for Hypotheses Generation
- **AF Unit (Right):** Abstract Argumentation Framework (AF/AA) for Hypotheses Argumentation

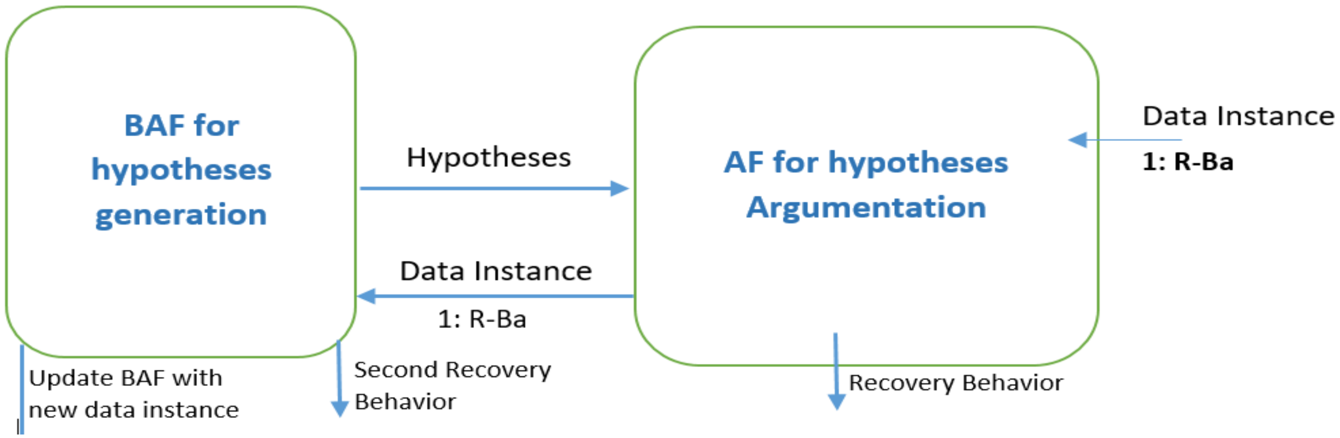


Example

- Colors (Red, Green, Blue, Yellow)
- Concept (Ball, Box, Person)
- Recovery Behaviors (Push, Ask, Continue, Alternative Route)
- The updating procedure for each unit



Time step	Color	Concept	Best Recovery Behavior
1	Red	Ball	Push
2	Red	Box	Alternative route
3	Red	Person	Ask
4	Green	Ball	Push
5	Green	Box	Alternative route
6	Green	Person	Ask
7	Blue	Ball	Push
8	Blue	Box	Alternative route
9	Blue	Person	Alternative route
10	Yellow	Ball	Push
11	Yellow	Box	Alternative route
12	Yellow	Person	Ask
13	None	None	Continue



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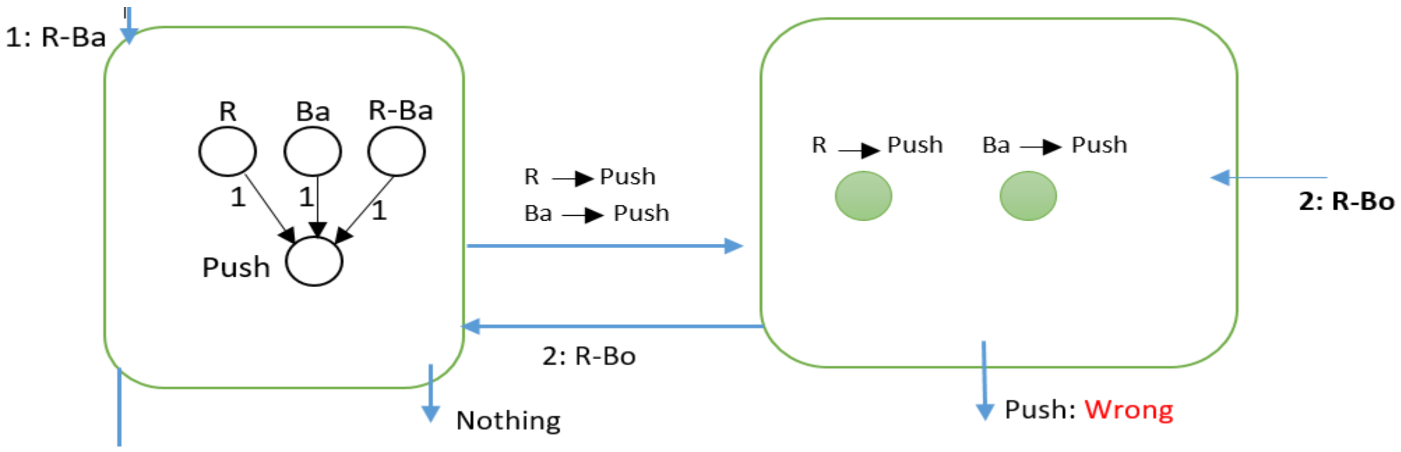

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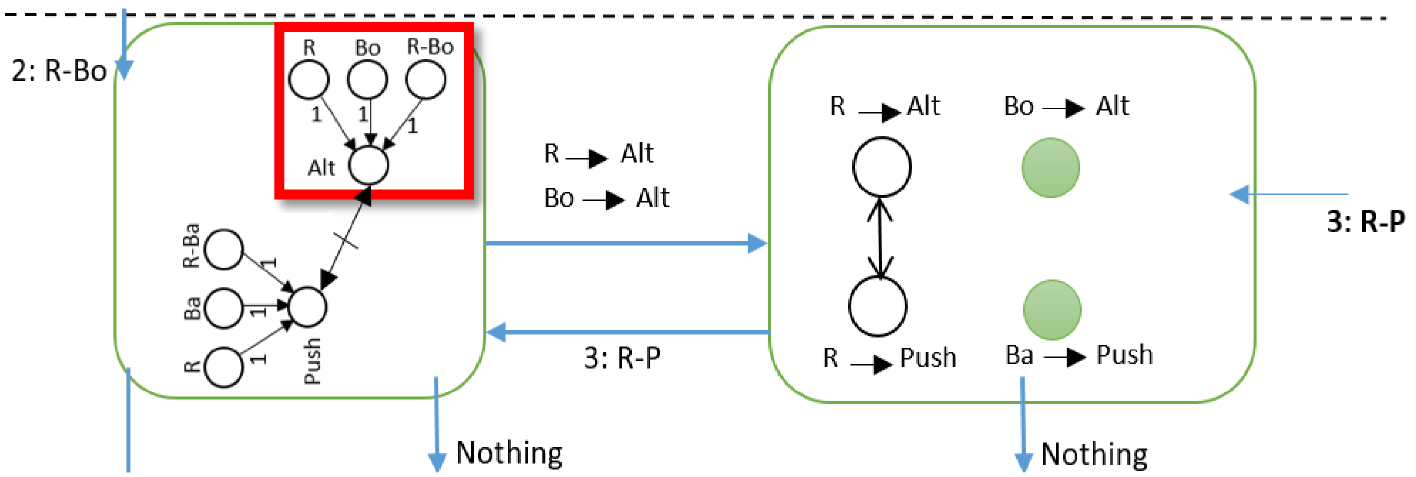

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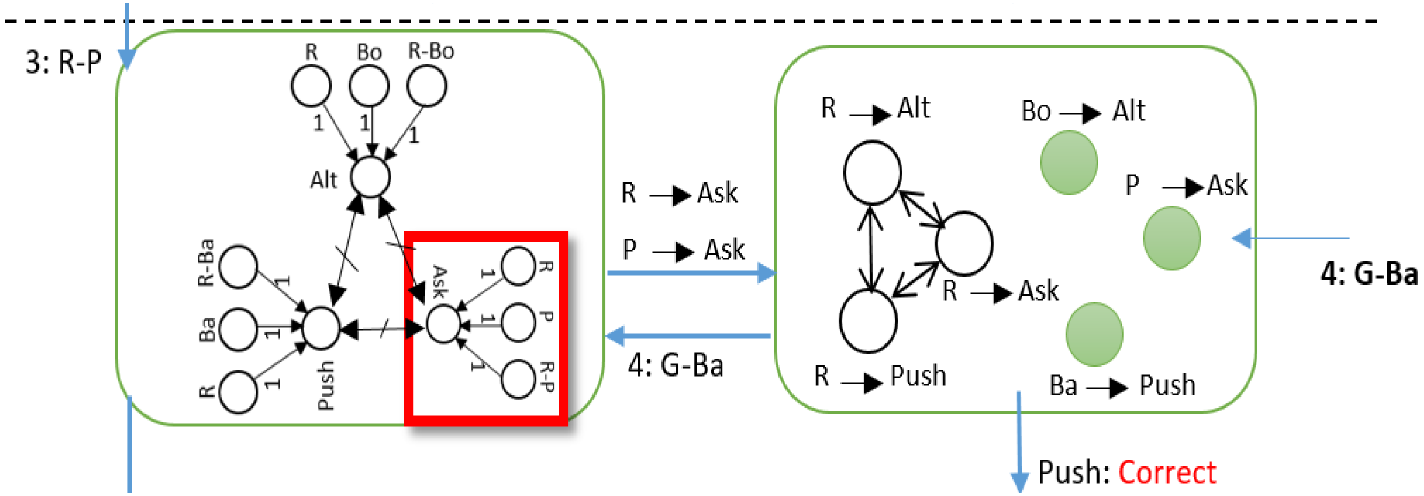

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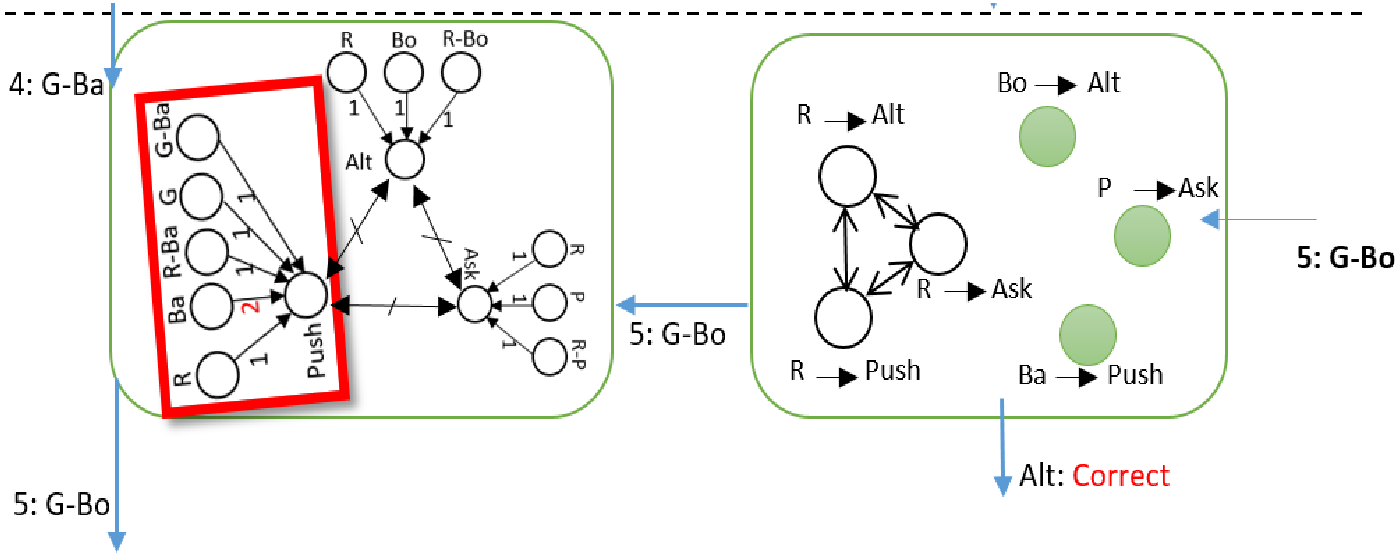

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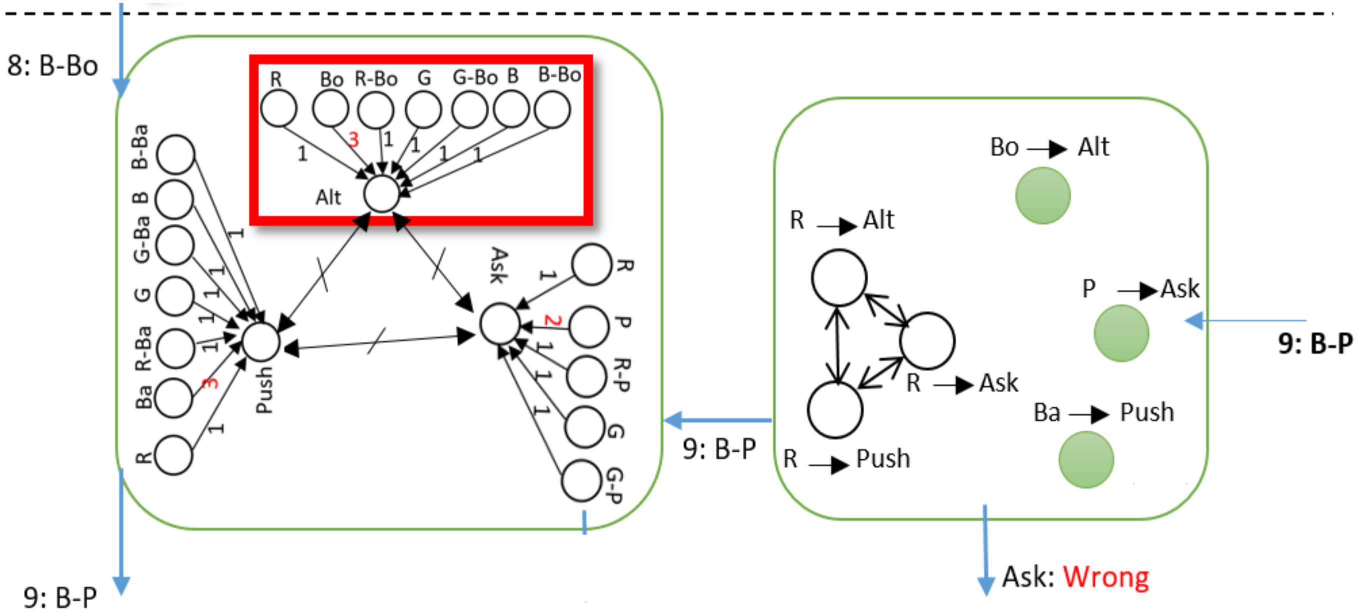

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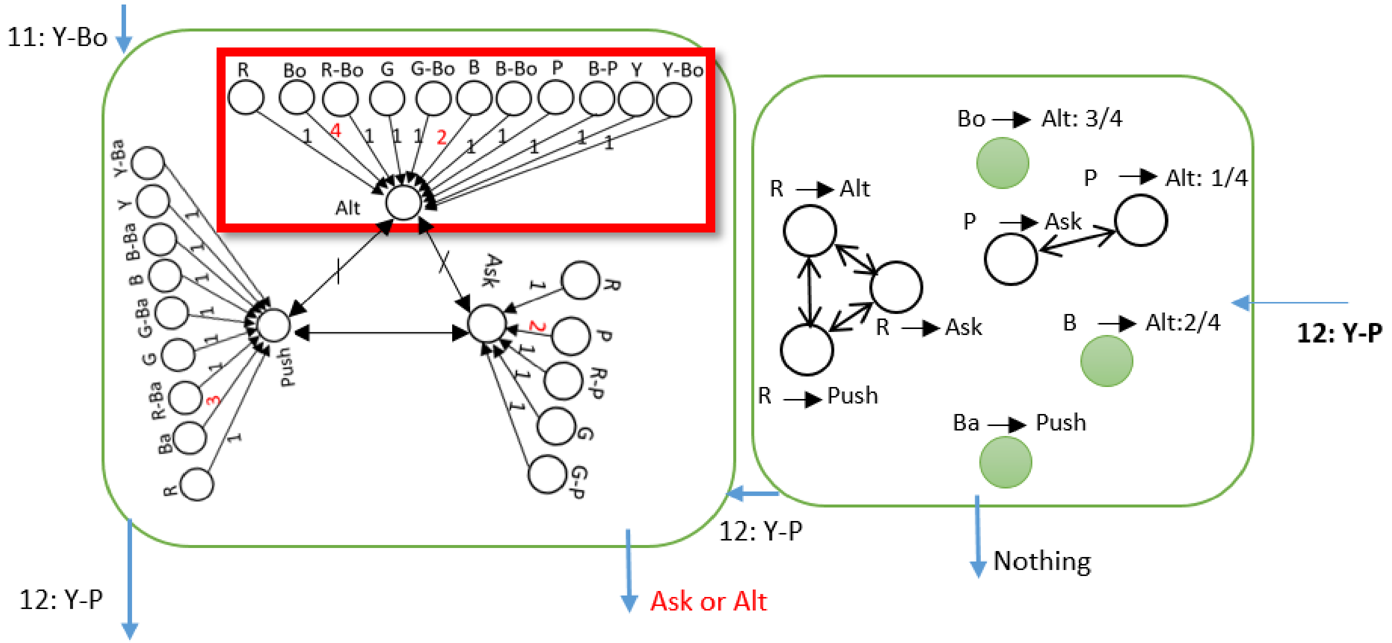

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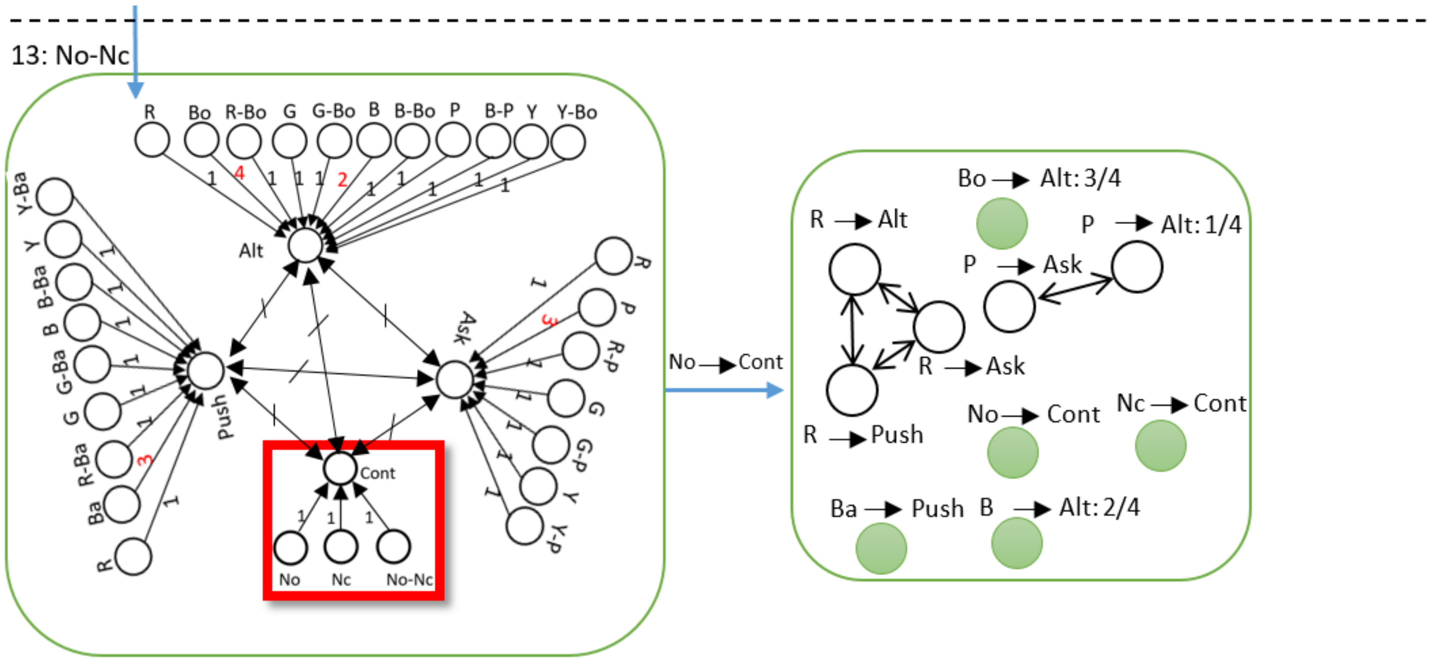

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9	Blue	Person	Alternative route
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11	Yellow	Box	Alternative route
12	Yellow	Person	Ask
13	None	None	Continue

Summary:

- At each point in the learning phase the most important set of hypotheses can be find in the grounded extension of the AF unit.
- For this case: 7 out of 13 was successfully classified.

Time step	Color	Concept	Best Recovery Behavior
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3	Red	Person	Ask
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9	Blue	Person	Alternative route
10	Yellow	Ball	Push
11	Yellow	Box	Alternative route
12	Yellow	Person	Ask
13	None	None	Continue

Comparisons

1. Online Incremental Learning:
    - Incremental Support Vector Machines (ISVM)
    - Online Random Forest (ORF)
    - Online Naïve Bayes
    - Neural Networks, Multi Layer Perceptron (MLP)
    - Decision Tree Based Methods
        - ID3
        - J48 is Based on C4.5
        - PART is Based on C4.5
        - PRISM
2. (Deep) Reinforcement Learning (RL)
3. Contextual Bandits (Associative Reinforcement Learning)

- List of Publications:

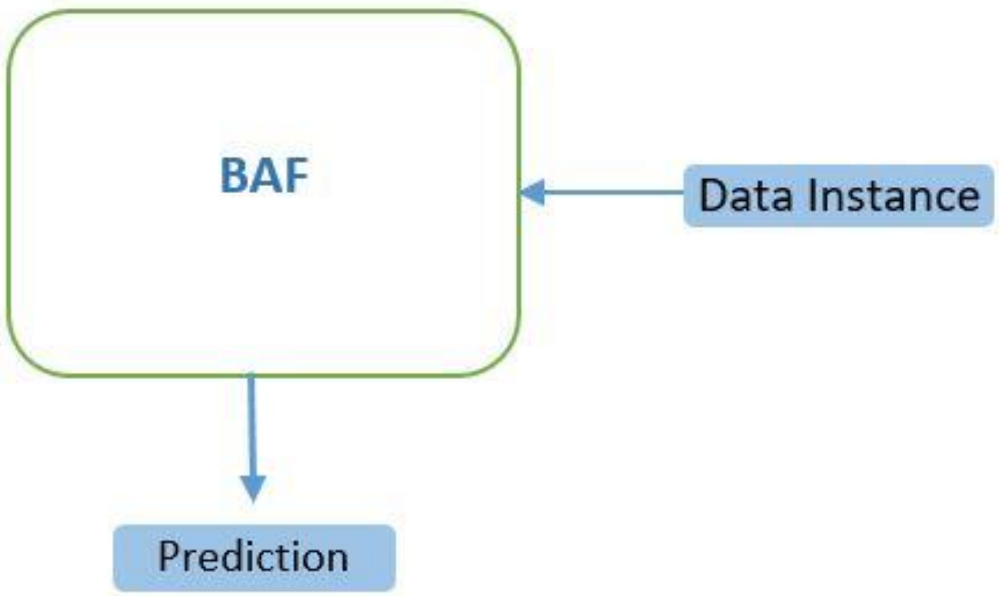
1. H. Ayoobi, M. Cao, R. Verbrugge, and B. Verheij. Handling unforeseen failures using argumentation-based learning. In 2019 IEEE 15th International Conference on Automation Science and Engineering (CASE), pages1699–1704, Aug 2019
2. H. Ayoobi, M. Cao, R. Verbrugge, and B. Verheij. Argumentation-based online incremental learning. IEEE Transactions on Automation Science and Engineering (TASE), 2021
3. H. Ayoobi, M. Cao, R. Verbrugge, and B. Verheij. Argue to learn: Accelerated argumentation-based learning. In 20th IEEE International Conference on Machine Learning and Applications (ICMLA)

The limitation of ABL

- ABL is designed to handle discrete feature spaces. Therefore, It cannot handle continuous features.
- The computational complexity is high. We have addressed this issue in our latest research by proposing Accelerated Argumentation-Based Learning (AABL)

Accelerated ABL

- Architecture: Only Bipolar Argumentation Framework



Accelerated ABL

Acceleration Strategies:

1) Feature-value subsets:

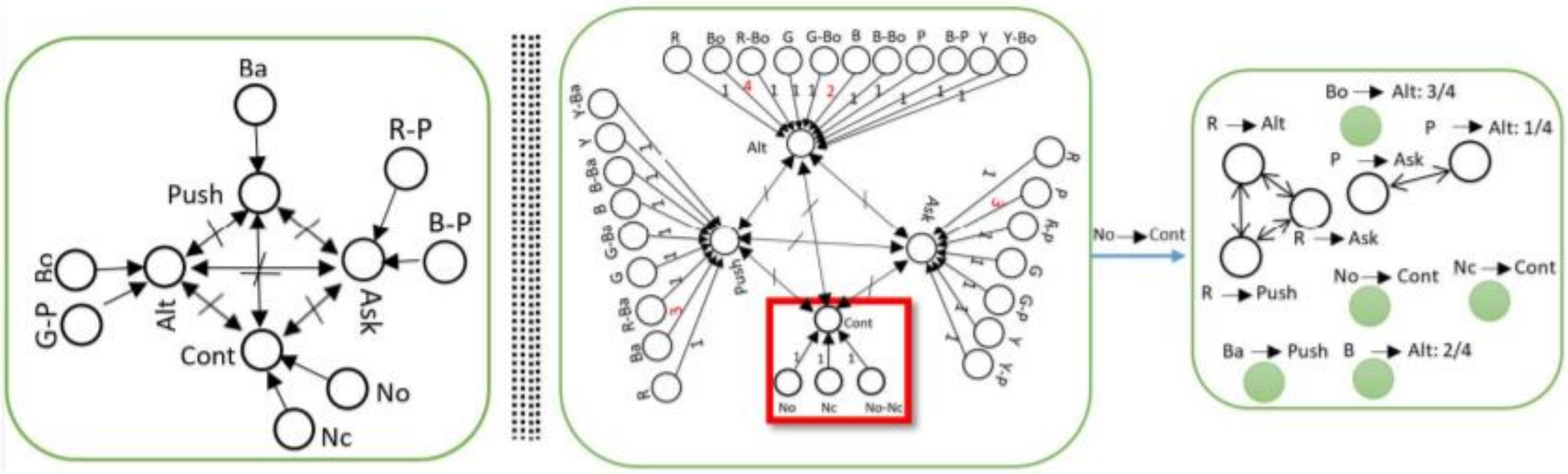
- Starting from subsets with length L=1 and increment the subset size if needed.
  - L is incremented under certain condition which occurs because of the pruning step.

2) Pruning the unnecessary supporting nodes from BAF:

- Including only unique supporting nodes.
  - A supporting node is considered unique if it only support one class label (recovery behavior).

Accelerated ABL

- Trained Accelerated ABL vs ABL model for a small example.



a) Our Approach

b) Original ABL approach [1], [2]

- 4 times lower nodes and relations.

Computational and Space Complexity

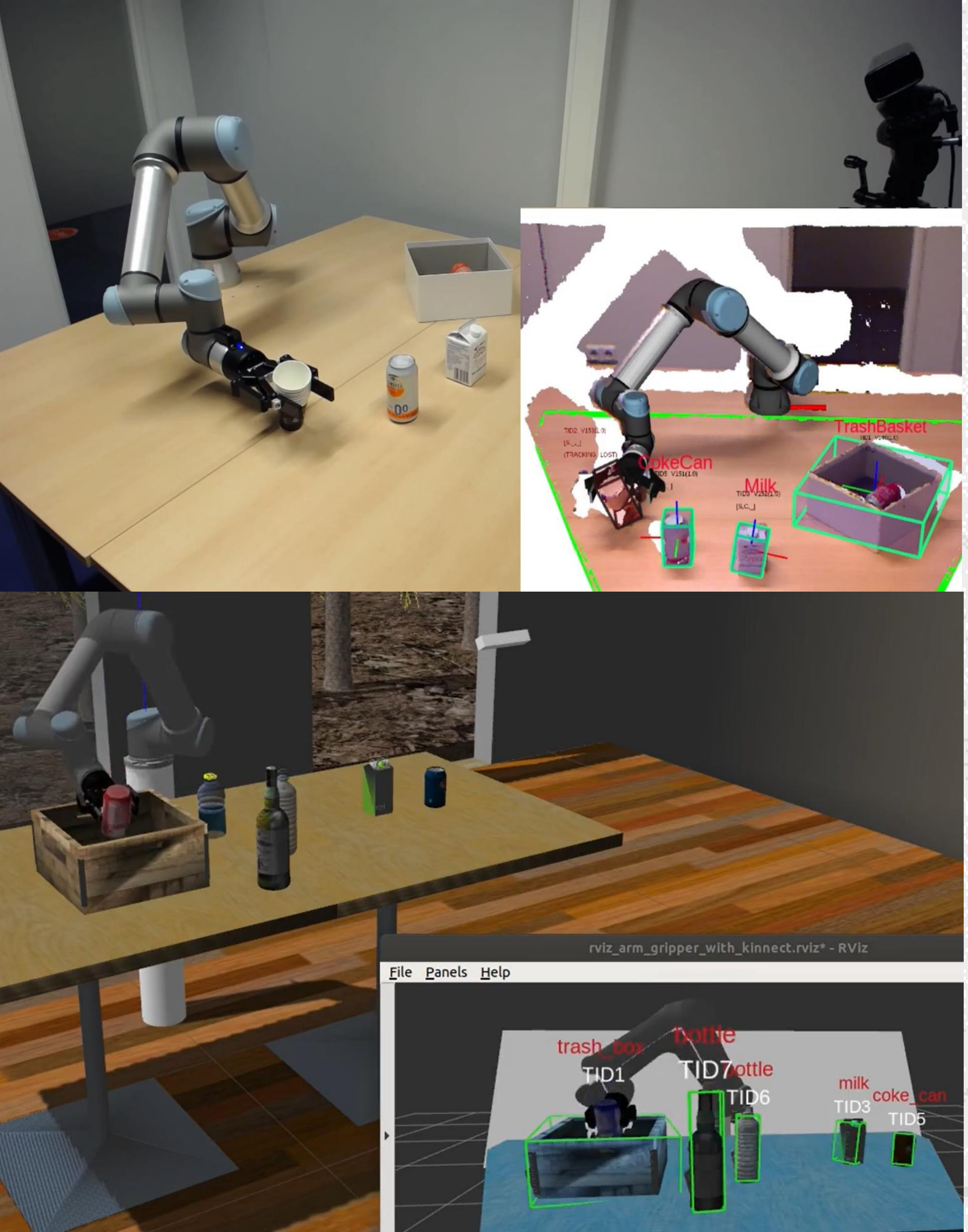
- Subset of length one vs all the power set:
  - **Accelerated ABL: (Polynomial)**
    - Scenario 1: O(n)
    - Scenario 2-3: O(n^2)
  - **ABL: (Exponential)**
    - Scenario 1-3: O(2^n)

Applications of ABL:

- ABL is an **machine learning algorithm** which can **autonomously** extract **a set of hypotheses to explain** the reasoning process**.**
- ABL can be used in **open-ended learning and offline supervised learning** as well as the **reinforcement learning scenarios**.
- The model can be updated **incrementally**.
- Argumentation is used for modeling the **defeasibility relation** in the **knowledge base of the agent.**
- ABL takes the **features dependencies** into account.
- Learning **faster** than other common techniques for online incremental supervised learning with **a smaller number of learning instances**.

Therefore, it can be used in:

- All offline supervised learning problems.
- Lifelong (open-ended / class-incremental learning)



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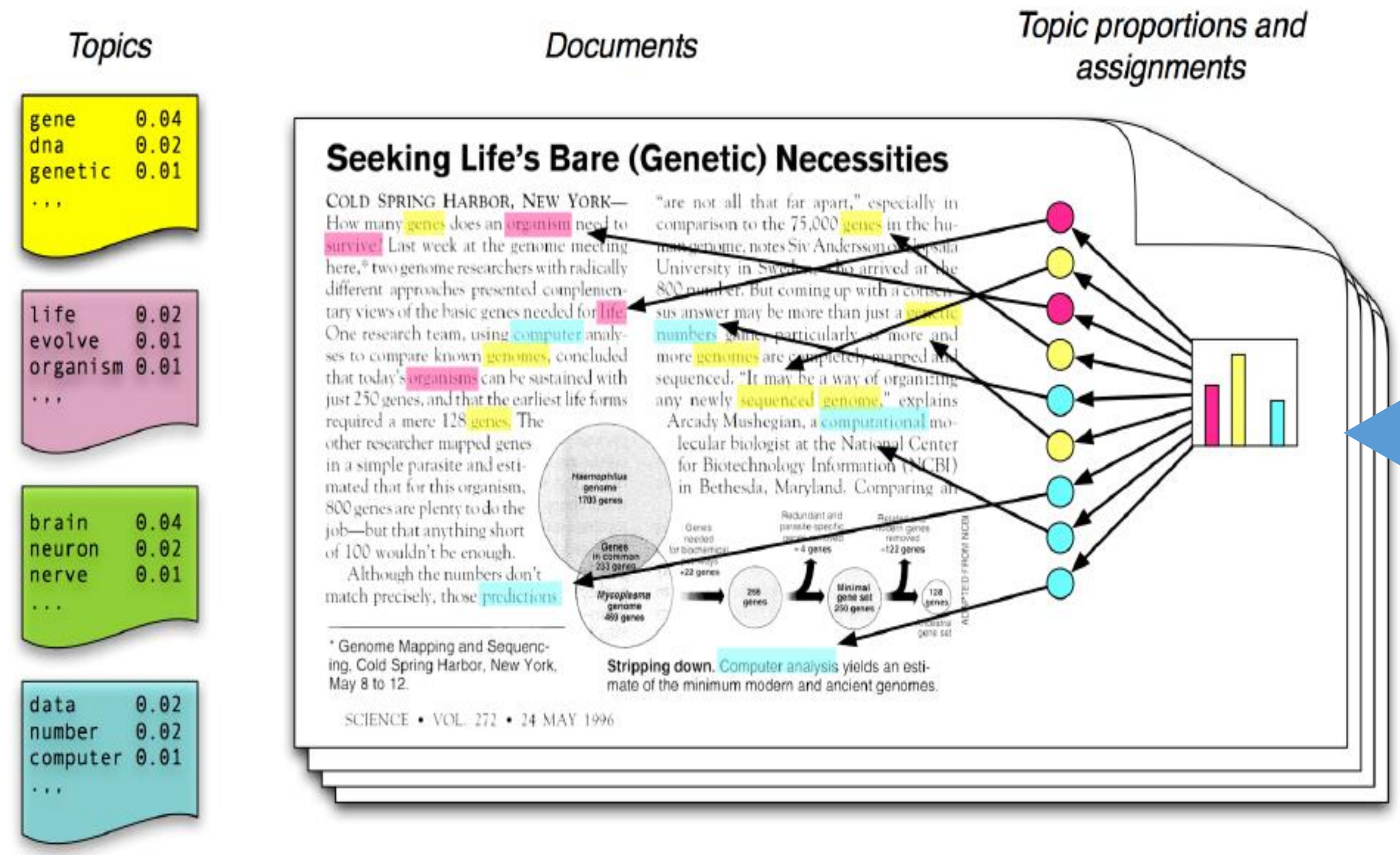
Local Hierarchical Dirichlet Process (Local-HDP)

Interactive Open-Ended 3D Object Categorization in Real-Time Robotic Scenarios



- Assume each document defines a distribution over (hidden) topics.
- Assume each topic defines a distribution over words
- The posterior probability of these latent variables given a document collection determines a hidden decomposition of the collection into topics.

So we have:

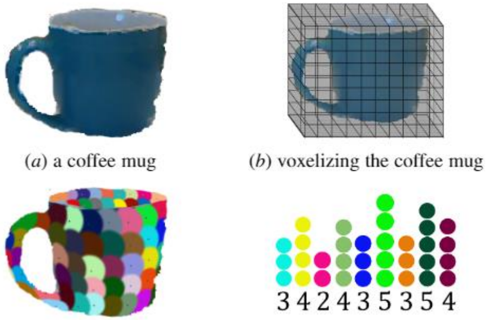
- Words
- Topics
- Documents
- Corpus

3D Object Category Recognition

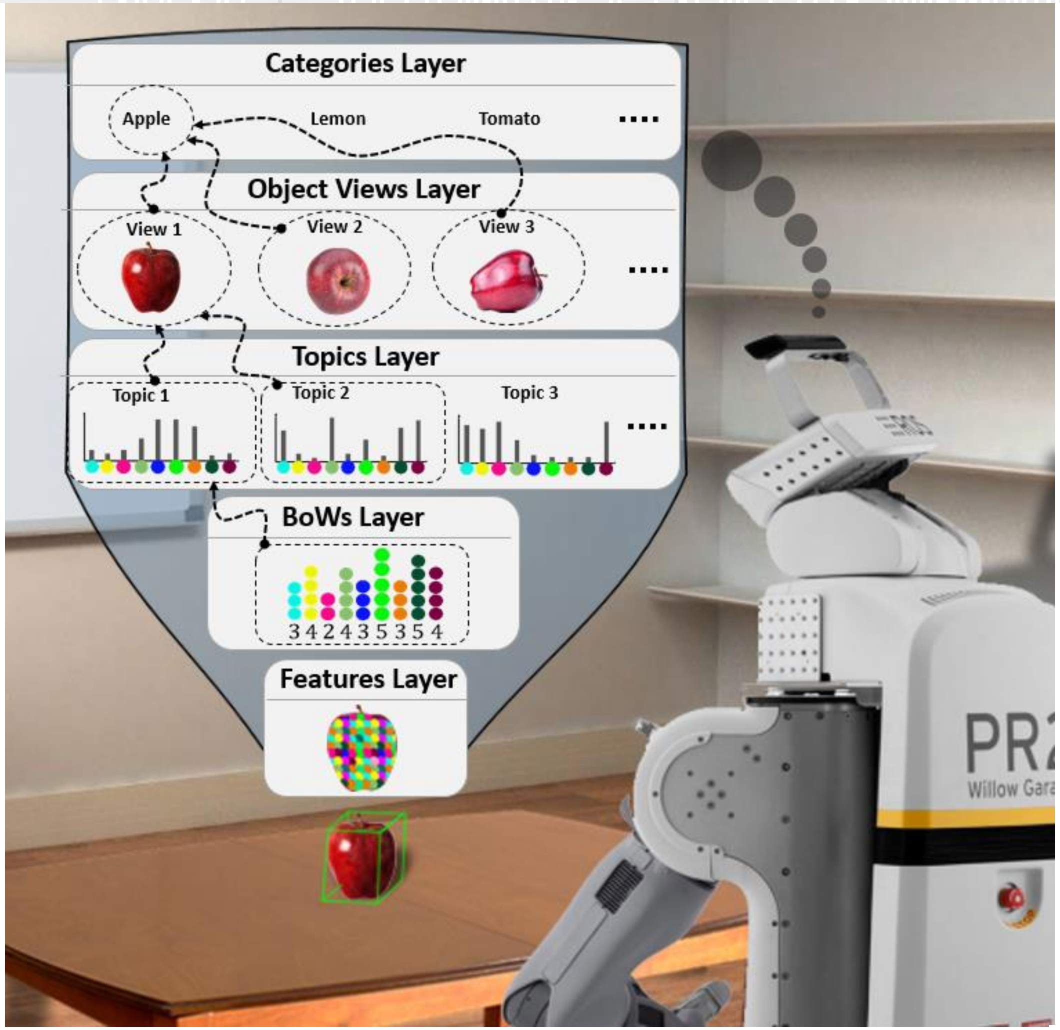
- Visual Words: Local-Shape Descriptor. (Spin-Images)
- Documents: Bag of Words layer
- Topics: Inferred latent variables showing the distribution of each document over visual words.
- Object Views: Point Cloud of Objects from different perspectives.
- Categories: Each Category contain different objects and each object has several object views.

(a) Intra-Category Variation

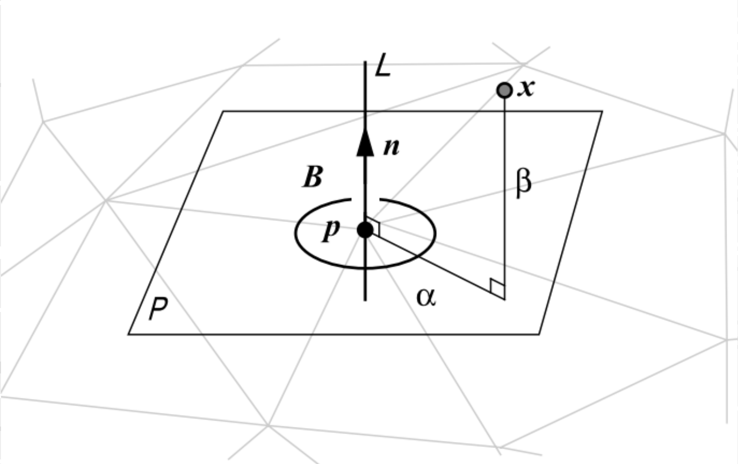
(b) Different Object Views



(a) a coffee mug
(b) voxelizing the coffee mug
(c) extracting local-features
(d) BoW representation

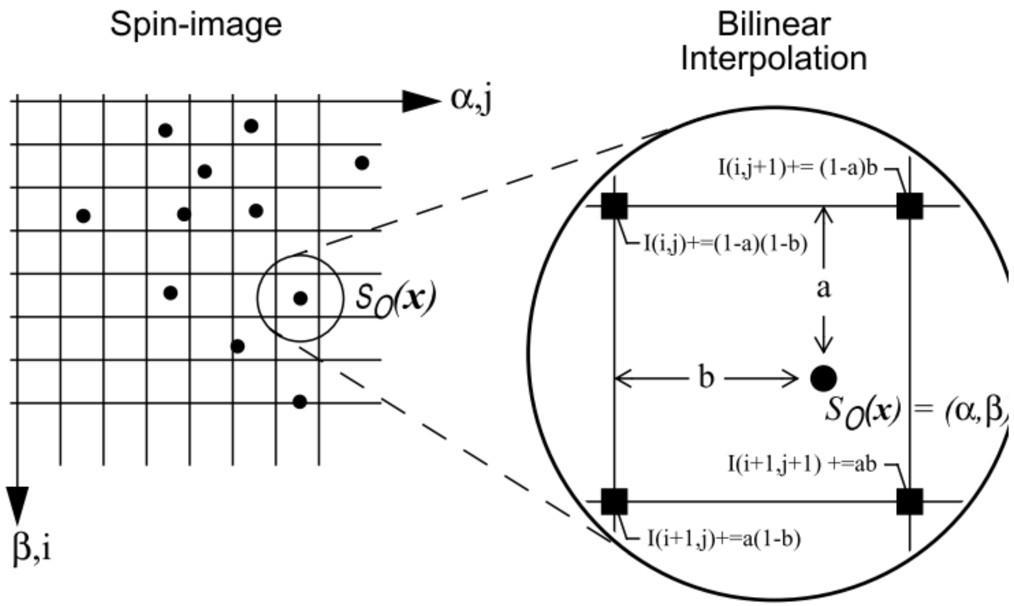


Spin Images as a Local Object Descriptor



Spin-Images are constructed by:

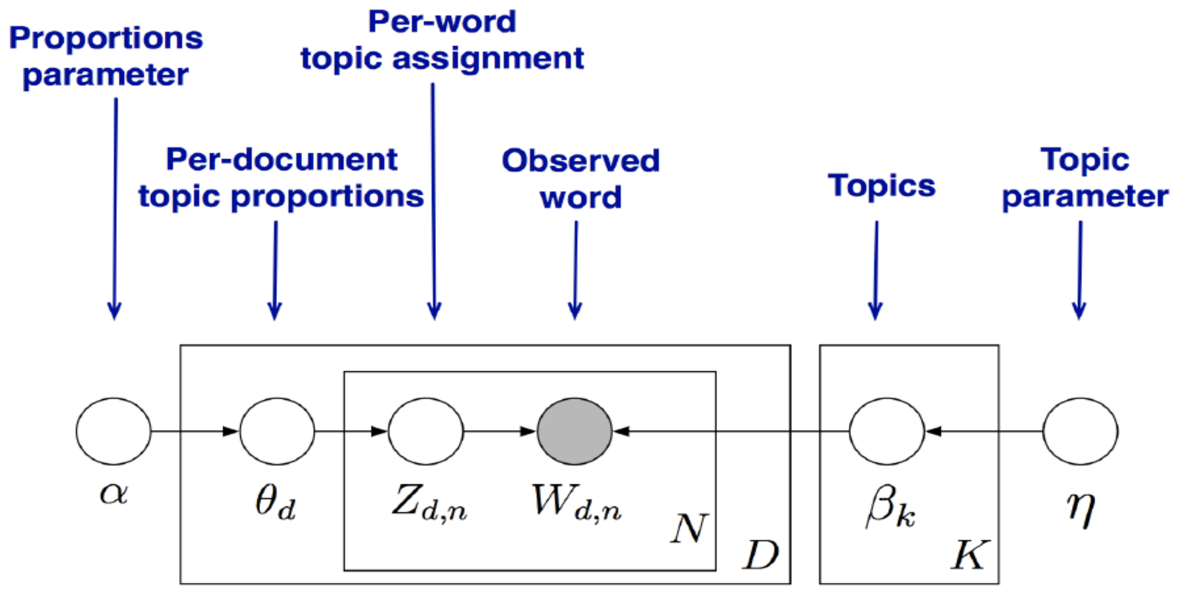
- Computing the surface normal for each point. (Oriented Point)
- Project the points to the tangent plane and find (α, β)
- Spread the location of the point in the 2-D array



Generative Model:

- We have the *bag-of-words* assumption (Order of the words are not important)
- In probability, we call it *exchangeability* assumption

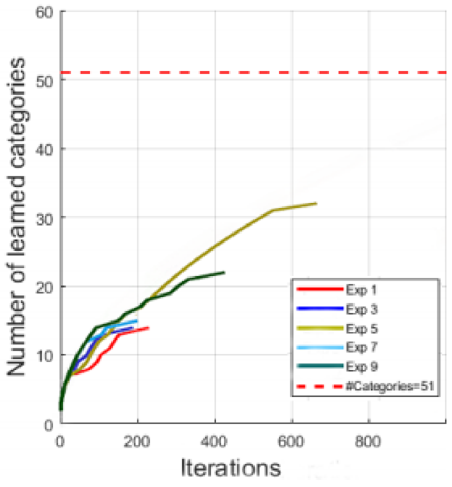
$p(w_1,\ldots,w_N) = p(w_{\sigma(1)}),\ldots, p(w_{\sigma(N)})$ (σ: permutation)

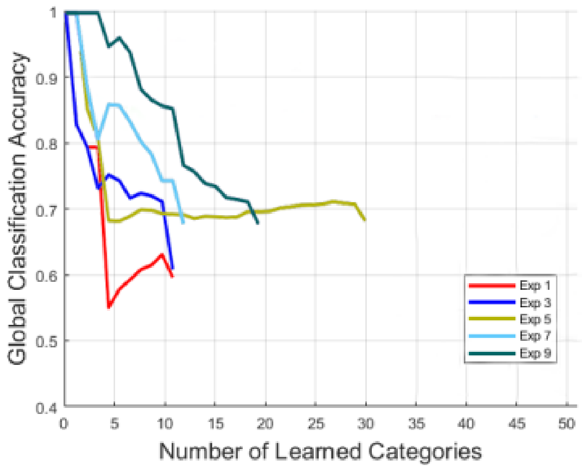


$$p(\beta,\theta,z,w|\alpha,\eta) = \prod_{i=1}^{K} p(\beta_i|\eta) \prod_{d=1}^{D} p(\theta_d|\alpha) \left(\prod_{n=1}^{N} p(z_{d,n}|\theta_d) p(w_{d,n}|\beta_{1:K}, z_{d,n}) \right)$$

Experiments

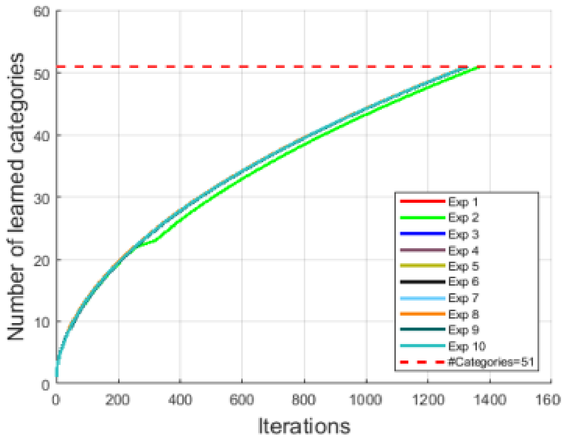
Exp#	#QCI	#LC	AIC	GCA (%)
1	811	**32**	10.19	71
2	654	30	9.40	70
3	514	28	8.07	72
4	696	**32**	8.59	**74**
5	579	27	9.14	71
6	505	24	8.91	71
7	697	30	9.40	72
8	550	25	9.92	68
9	560	**32**	10.19	72
10	564	28	8.92	70
Avg.	613	**28.50**	**9.08**	**71 %**

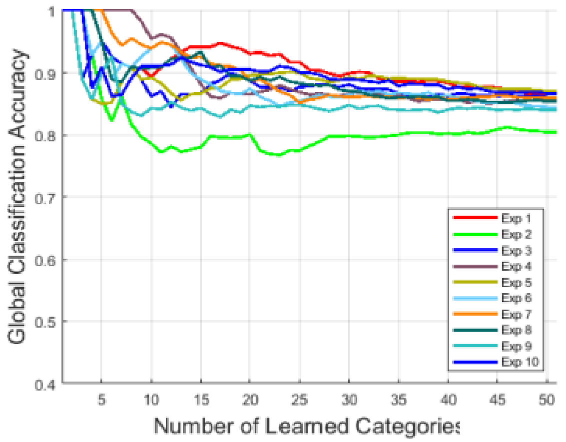




(a) Summary of experiments for Local-LDA sing collapsed Gibbs sampling

Exp#	#QCI	#LC	AIC	GCA (%)
1	1325	**51**	6.45	86.72
2	1370	**51**	8.25	80.44
3	1325	**51**	6.62	86.04
4	1325	**51**	6.70	85.74
5	1325	**51**	6.37	**87.02**
6	1325	**51**	7.03	84.45
7	1325	**51**	6.64	85.96
8	1325	**51**	6.80	85.36
9	1330	**51**	7.17	83.98
10	1327	**51**	6.47	86.66
Avg.	1330	**51**	**6.85**	**85.23 %**





(d) Summary of experiments for Local-HDP approach (our approach)

- List of Publications:
  - Hamed Ayoobi, H Kasaei, Ming Cao, Rineke Verbrugge, and Bart Verheij. Local-HDP: Interactive open-ended 3D object category recognition in real-time robotic scenarios. Robotics and Autonomous Systems (RAS), 147:103911, 2022

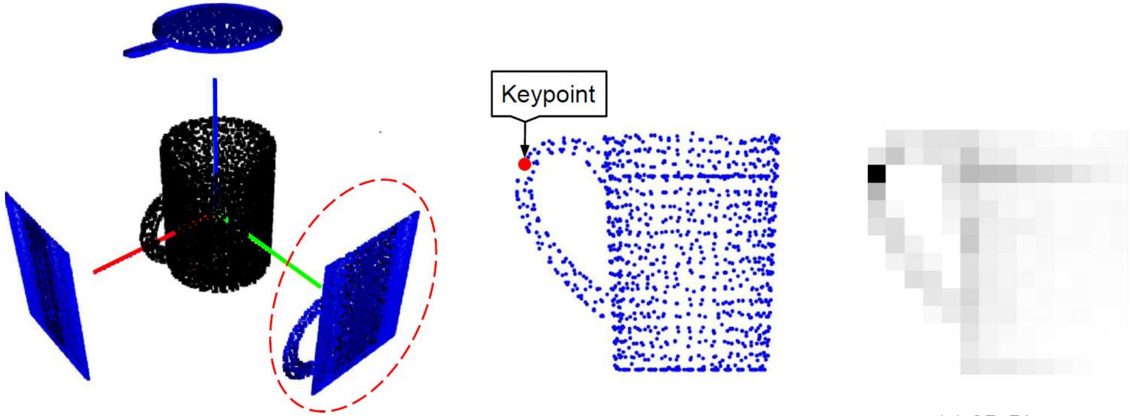
Local Hierarchical Dirichlet Process (Local-HDP)

3D Object Parts Segmentation

3D Object Parts Segmentation

- Visual Words:
    - Local-to-Global Descriptor. (Spin-Images)
    - Global-to-Local Descriptor. (GOOD)
- Documents: Bag of Words layer
- Topics: Inferred latent variables showing the distribution of each document over visual words.
- Object Views: Point Cloud of Objects from different perspectives.
- Object Parts: Segmenting a 3D object to a set of semantic parts.

(a) A Keypoint's Normal (b) Local-to-Global Spin-image (c) 2D Bins



(a) Global Projections (b) Keypoint on the Projection (c) 2D Bins

Segmentation Results:

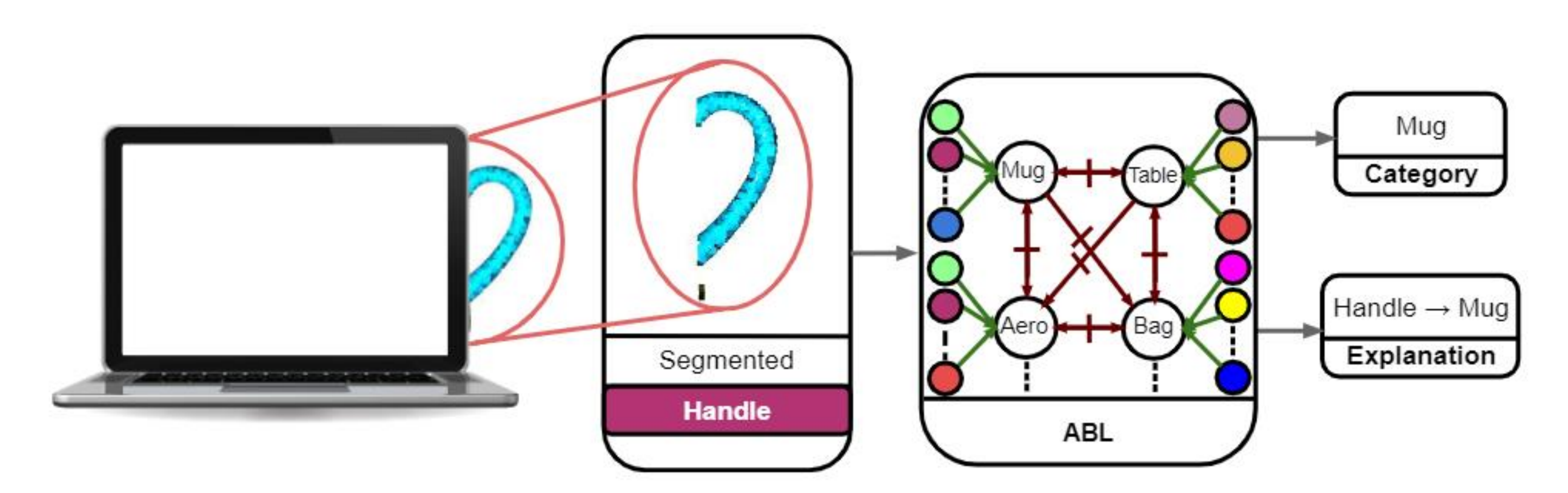
Imperial College London

university of groningen / faculty of science and engineering / bernoulli institute

Explain What You See

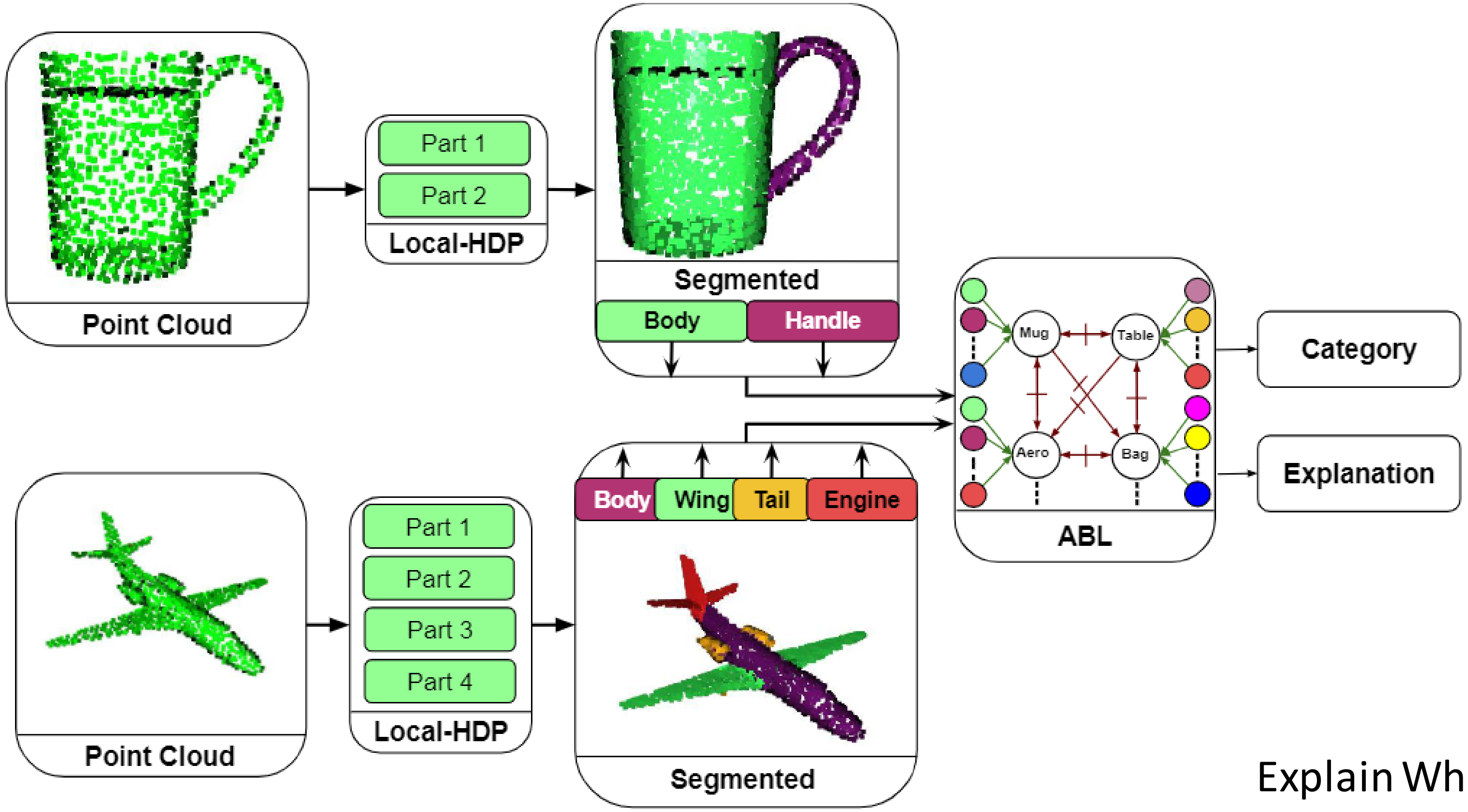
3D Object Recognition using ABL and Local-HDP

Researchers: Hamed Ayoobi
Hamidreza Kasaei
Ming Cao
Rineke Verbrugge
Bart Verheij



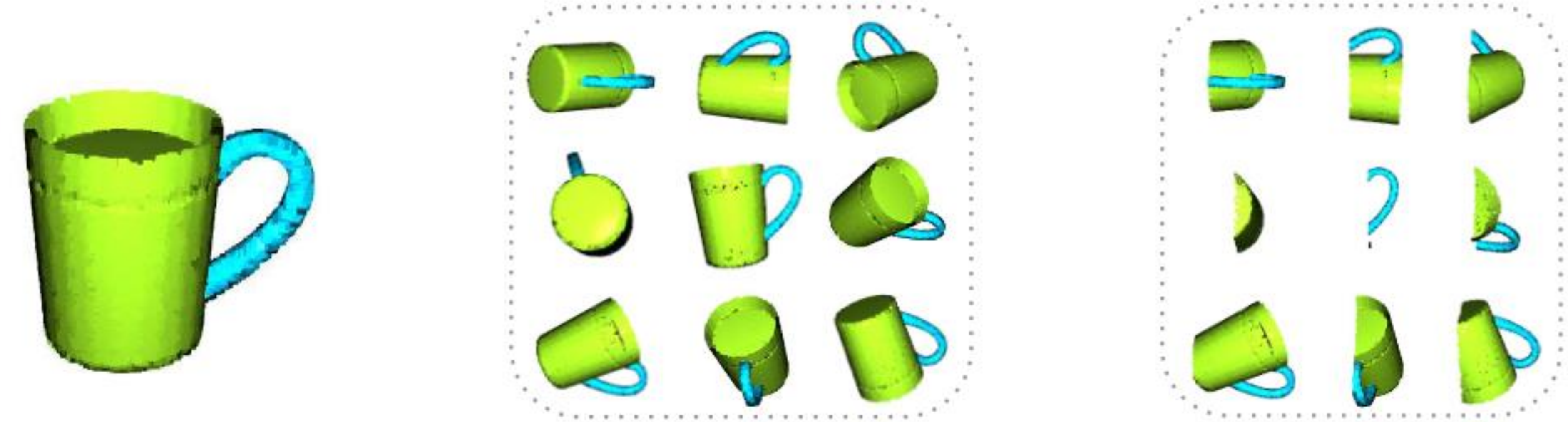
Architecture

- Integrating Argumentation Based Learning (ABL) with Local Hierarchical Dirichlet Process (Local-HDP) for 3D object parts Segmentation



Occlusion:

- Most of DNNs in the literature does not work well with high degree of occlusion.
- Constructing a dataset for occlusion based on ShapeNet core dataset.



(a) Mug (b) Random Rotations (c) Random Cuts (Simulated Occlusions)

Explainability:

- In this research, the power of argumentative explanations improved the model to classify occluded object.
  - The learning accuracies shows that explainability made the model more robust to missing data
- Explainability for zero-shot learning:
  - Imagine that the model is trained with **Cup** that has **no handles**, and with **teapots** and **pitchers** that have **handles.**
  - What happens if we show an unforeseen Mug with a handle to the model?
    - Probably misclassification: since it has a handle, it is more probably to be classified as a teapot or pitcher.
  - Using argumentation-Based Learning, we can teach the model with a rule like the following one and the model can detect the new type of mugs afterwards without previously seeing them (zero-shot learning).
    - The ABL model should previously learned **Cup's Body → Cup**
    - User injects this rule: **Cup's Body and a Handle → Mug** and the model learns to classify unforeseen category of mugs.

CONCLUSION

- Argumentation online Incremental Learning (ABL)
  - Learning with smaller number of learning instances
  - Higher final learning accuracy
- Local Hierarchical Dirichlet Process (Local-HDP)
  - Category recognition for 3D Objects
  - 3D Object Parts Segmentation
    - Both have a higher learning precision
    - Both are applicable in open-ended scenarios
    - Both work for real-time robotic applications.
- Integrating ABL and Local-HDP
  - Handle High degree of occlusion
  - Provide explanations for the reasoning process

Future works:
Human in the loop, debugging the model with user interactions.