OpenLabCluster: Semi-automatic Keypoints Based Animal Behavior Clustering and Classification

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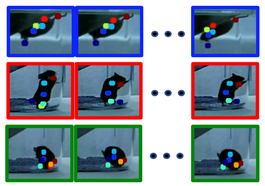
Animal Behavior Identification

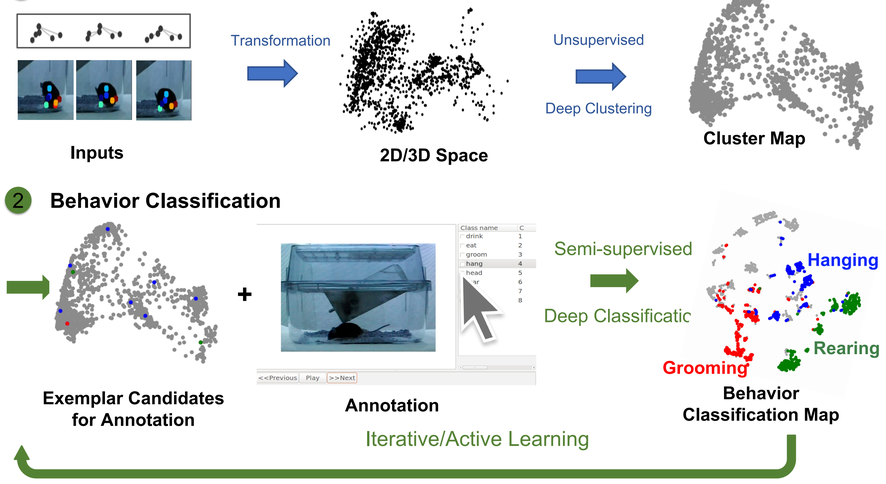
- Animal behavior identification: automatically discovering behavior repertoires during animal movements.
- Application of behavior identification: physical health condition monitoring, discovering stimuli induced prototypical reactions and occurring orders, and studying behavior and neuron activity interaction.
- Unsupervised behavior identification: cluster samples in the reduced dimension space. fully automatic without the guarantee of the semantic meaning and behavior granularity.
- Supervised behavior identification: rely on annotated samples, annotations are subjective and error prone, besides, annotation is time consuming.
- The proposed system, "OpenLabCluster", using Active Learning (AL) enhanced semi-supervised learning methods, learns to identify desired behavior repertoires with a few annotated samples.

OpenLabCluster: Semi-supervised Behavior Identification

- OpenLabCluster is embedded in an GUI taking inputs: i) time-series keypoints ii) processed kinematics features.

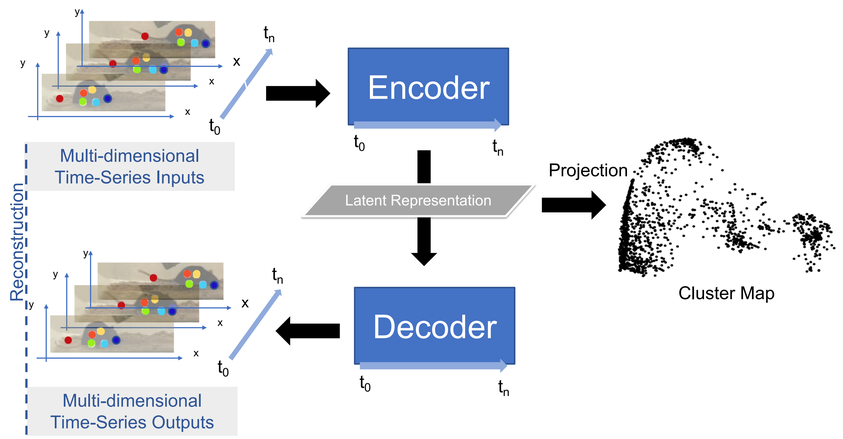


- It performs behavior identification in two stages, i.e., Behavior Clustering and Behavior Classification.
- Behavior Clustering is an unsupervised learning stage. It learns the t transformation from the input space to the latent space. In the hidden space, representations of samples from the same cluster located in the nearby neighbours.
- Behavior classification are learned based on a subset of annotated samples. These samples are selected by the AL methods from the learned representations. In the behavior classification stage, sample selection, annotation and behavior classification are repeated for several iterations.



Behavior Sequence Clustering

- Transforming the time-series inputs into semantic meaningful latent representations is an essential stage of OpenLabCluster where later stages including AL and behavior identification are built on.
- Encoder-Decoder structure is used to learn the transformation.
- Encoder maps inputs to latent representations, decoder regenerates the inputs from latent representations.
- The encoder and decoder are learned by reducing reconstruction loss.
- Cluster map is the projection of latent space in 2D.



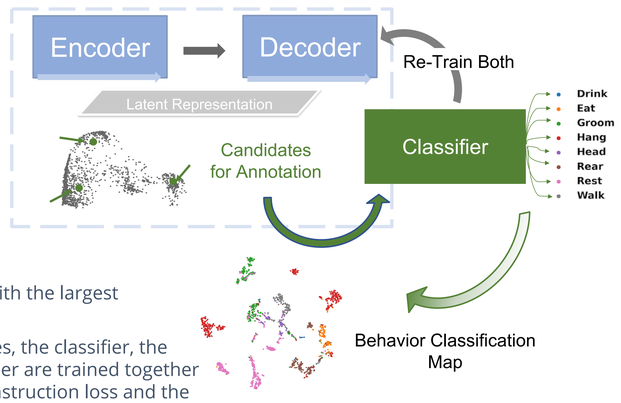
AL & Behavior Classification

AL methods select candidates for annotation based on the hidden representation.

Three AL methods:
TOP--selects samples at cluster center.
MI--selects uncertain samples according to classifier outputs.
CS—selects samples with the largest covering radius.

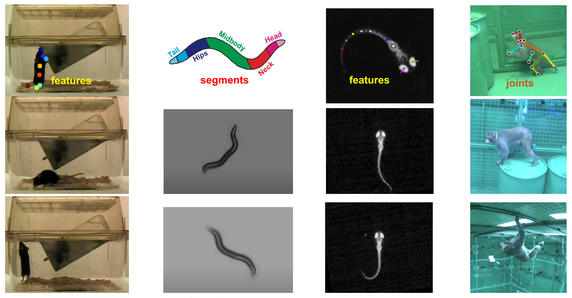
With annotated samples, the classifier, the encoder and the decoder are trained together to minimize both reconstruction loss and the classification loss.

Sample selection are performed in several iterations with the relearned latent representations.



Animal Behavior Datasets

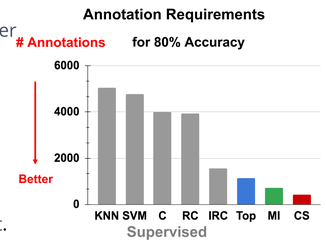
The effectiveness of OpenLabCluster is demonstrated through animal movements dataset with 4 different species.

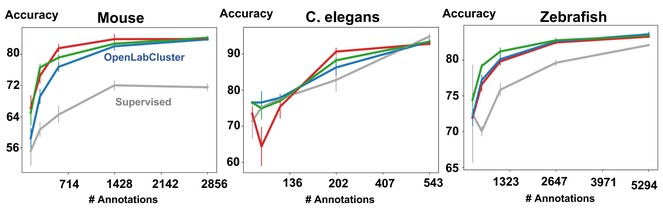


Evaluation

i) By inspecting the required number of annotations to achieve 80% accuracy, we can see AL methods including TOP, MI and CS require much less annotated samples.

ii) OpenLabCluster associated methods outperforms supervised methods across annotation budget.





Conclusion

- A semi-supervised active learning framework, OpenLabCluster, for behavior identification is proposed which can achieve satisfying performance with less annotations compared to supervised methods.
- OpenLabCluster learns behavior identification in two stages: behavior clustering and behavior classification.
- Behavior clustering maps time-series inputs into organized latent space using the encoder-decoder network.
- The classifier learns to classify behaviors from AL selected and annotated samples and transfer the knowledge to other unlabeled samples to make predictions.

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