Unsupervised Continual Learning (UCL)

Team

- Font colours: Tomas black; Yaw Hon blue, Ellie Dickens green, Mohanad purple, Nathan orange.

Abbreviations

CL	Continual Learning
DR	Dimensionality Reduction
QE	Quality Estimation
SOTA	State-of-the-art
UCL	Unsupervised Continual Learning
UL	Unsupervised Learning

Initial Brainstorm

- Motivation: continual learning for camera trap data without supervised learning. The system learns about different "entities" based on similarities/differences, without any supervised learning. For example: input → 100,000 camera trap images; output → images organized into x different categories. This is of course a form of clustering, but with some differences in relation to traditional clustering: (1) endless context, (2) open-ended number of categories/clusters, (3) possible inclusion of identification (e.g. is this the same elephant to passed here 2 days ago).
- A comparison of unsupervised learning (UL) techniques for image classification.
- Compare x UL tecs. applied to classic datasets (e.g. MNIST).
- Conditions:
    - Condition A: standard supervised learning.
    - Conditions B: (1) apply UL tecs., (2) add labels after the clustering, (3) compute accuracy. Point 2 might have some issues (for example, in the case of MNIST, what happens when the number "8" gets assigned to two or three clusters? Which cluster gets the number 8? Maybe the largest cluster can get number 8, and the remaining get "unknown" which by default is incorrect. As such, if all digits formed two clusters of equal size, then the accuracy of the UL technique would be 50%. To give another example, if all digits formed multiple clusters,

    whereby the largest cluster for each digit contained 80% of the instances, then the resulting accuracy would be 80%.
        - Alternatively each cluster can be labeled by the category with the majority of instances in the cluster. As such if the number "8" has 3 clusters, and 2 of these clusters have a majority of 8 instances, then these two clusters will be labeled with "8". This is fairer than using an "unknown" label, and should actually lead to higher accuracies. However, it could lead to a degenerate case with a very large number of clusters. Think.
    - Conditions C: (1) apply UL tecs., (2) convert cluster labels into true labels (can be problematic for over-clustering, etc.), (3) create dataset for supervised learning, (4) train a CNN in a supervised manner, (5) compute accuracy.
- Compare all conditions A, B, and C.
- Different constraint dimensions:
    - Data inspection. At one extreme, allow algorithms to inspect the dataset any number of times. Images can be seen and re-seen any number of times, and in any order. At the oher extreme, allow algorithms to inspect images only once (as they are seen for the first time).
    - Memory limits. At one extreme, allow algorithms to grow in memory (e.g. number of prototypes and/or number of parameters), and at the other extreme force memory capacity to be fixed.
    - Labeling information. At one extreme, forbid any form of labeling (pure UL), and at the other extreme allow (at the very most) some forms of weak supervision.
- Bio-inspiration, e.g.:
    - Jeff Hawkins et al's ideas, e.g.: the brain as a prediction machine. More learning guidance needs to come from "internal predictions". This is a form of labeling. This is related to self-supervision. Has the idea of self-supervision been explored sufficiently in the context of vision problems? Also, can columns and min-columns help? And frames of reference?

Think

- Th1 - Consider adding an active learning element. Active unsupervised continual learning (AUCL).

Notes

- UCL generalizes observation segmentation, e.g.:
    - Input: sequence of camera-trap frames.
    - Output: specimen A, specimen A, specimen B, specimen B, specimen A, etc. Observations can be segmented at the boundaries of different specimens.

Open Problems

- Adaptive numbers of clusters.
- Endless number of clusters, and implications to memory and efficiency.
    - Use dimensionality reduction to get a compact representation, and use some form of hashing (etc.) for more efficient computation? What SOTA solutions currently exist for making prototype-based approaches more efficient?
- Continual learning.

Potential Sub-Projects/Papers

- SP1. (3-5 months - depending on prior experience) Experimental variation 1.
    - Key focus: SOTA UCL methods.
- SP2. (3 months) Experimental variation 2.
    - Key focus: Adapting UL to CL.
- SP3. (3 months) Review paper: "adaptive cluster numbers" + k-means.
    - Key focus: review paper of adaptive k-means.
- SP4. (3 months) Comparison study of "adaptive cluster numbers" k-means variations, with potential innovations.
    - Key focus: experimental comparison of adaptive k-means.
- SP5. (3 months) (Yang et al. 2017) (or another approach that jointly learns dimensionality reduction (e.g. autoencoder) and k-means clustering; or if not "joint learning" at least coupled/related at some level) adapted for continual learning.
    - Key focus: DR and prototype-based clustering.
    - [DO - 0% - Check in-citations: has anyone extended this for continual learning?]]
- SP6. (3 months) Systematic experiments with different pre-trained networks (and different extraction approaches) for feature extraction for k-means (or related approaches), possibly combined with different distance metrics, in the context of auto-curation (observation segmentation and clustering).
    - Key focus: pre-training + feature extraction + prototype-based clustering.
- SP7. (3 months) A simple study of the application of different UL techniques to 3 different aut-curation related datasets (i.e. raw citizen science photographs (pre-curation), camera trap data (pre-curation), iNaturalist data (post-curated)). Performance metrics: observation segmentation, "clustering accuracy", etc.
    - Key focus: UL applied to small subsets/batches (e.g. 500-10,000 images) of auto-curation datasets (no CL).
- SP8. (3 months) AI4 consolidation/wrap-up.
    - Reserved for Yaw Hon.
    - See description here.
    - Key focus: (1) minimalistic "UL to CL" (more focused than SP2; related to batch clustering), (2) simple QE with at least one DL model, (3) integration of UL2CL and QE for auto-curation.
- SP9.

    - Brief description. Similar to SP8 (ideally building from SP8) but focusing on novelty detection. In other words, in this sub-project we investigate how different novelty detection algorithms (e.g. “image x does not belong to any of the existing clusters → create a new cluster) can improve the UL+CL performance of SP8. This is clearly related to the problem of “adaptive k-means”, however, the focus is on novelty estimation, which has its own literature. See GSS ["novelty detection" inaturalist] --> 37 results.
    - Key focus: novelty detection + (UL+CL).
- [DO - specify more details] (3 months) A study on approaches for making prototype-based clustering more efficient (in terms of memory and speed) in the scale of 1000s or 10,000s of classes.
- [See more - A Survey of Clustering With Deep Learning: From the Perspective of Network Architecture]

Literature

Misc

- Have a look at: Wildlife video key-frame extraction based on novelty detection in semantic context.

Unsupervised Learning + images + DL + recent SOTA

- Misc.
    - Interesting and useful papers.
        - SCAN: Learning to Classify Images without Labels with code here.
        - Unsupervised Deep Learning via Affinity Diffusion.
    - Useful survey. A Survey on Semi-, Self- and Unsupervised Learning for Image Classification
- GSS [intitle:"joint clustering" images biodiversity] → 0 results
- GSS [intitle:unsupervised intitle:clustering "unsupervised learning" images classes github clustering clusters ("deep learning" OR "convolutional neural" OR "neural networks")], since 2020 → 58 results
- GSS ["SCAN: Learning to Classify Images without Labels" clustering github], since 2021 → 57 results

Unsupervised Learning + biodiversity images

- Note. It might be interesting to compare pure UL applied to only images vs applied to images together with time stamps. The temporal adjacency of photographs and/or frames can be used to further disambiguate clusters. Photographs and/or frames taken close in time are more likely to belong to the same observation/cluster.
- GSS ["unsupervised learning" images biodiversity] → 2,160 results.

- Notes:
  - There are probably more papers here than I expected, in a broader range of biodiversity applications than I expected too (e.g. estimation of number of species in a location).
- Examples:
  - Pantazis, O., Brostow, G.J., Jones, K.E. and Mac Aodha, O., 2021. [Focus on the positives: Self-supervised learning for biodiversity monitoring](). In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 10583-10592).
    - This is more about learning good representations for downstream tasks (e.g. classification).
  - Rama Rao, K.V.S.N., Garg, S. and Montgomery, J., 2018, December. [Investigation of unsupervised models for biodiversity assessment](). In Australasian Joint Conference on Artificial Intelligence (pp. 160-171). Springer, Cham.
    - Interesting research on using a clustering approach for assessing the number of bird species (and other variables) in an area, based on acoustic signals.

UCL

- The area of UL is very large and old, and the notes above probably are not pointing to anything new. Check the literature: has a simple study comparing A, B, and C been done before?
  - GSS ["unsupervised learning" ("continuous learning" OR "continual learning" OR "open-ended learning") image classification] → 2,960 results
  - Add camera-traps → GSS ["unsupervised learning" ("continuous learning" OR "continual learning" OR "open-ended learning") image classification (camera-trap OR camera-traps)] → 4 results. Example:
    - https://link.springer.com/article/10.1007/s13218-020-00631-4
    - “Self-reinforcing Unsupervised Matching”
  - GSS [intitle:unsupervised "unsupervised learning" ("continuous learning" OR "continual learning" OR "open-ended learning") image classification] since 2019 → 90 results
    - Very relevant (ordered from most relevant to least relevant (according to a superficial guess); note that the the papers at the end of this list are still relevant):
      - [continue here - 10% - read completely] [Online Unsupervised Learning of Visual Representations and Categories]()
      - [Unsupervised Continual Learning Via Pseudo Labels]()
      - [Unsupervised Image Matching and Object Discovery as Optimization]()

                - M. Cho, S. Kwak, C. Schmid, and J. Ponce. Unsupervised object discovery and localization in the wild: Part-based matching with bottom-up region proposals. In CVPR, 2015.
                - Rethinking the Representational Continuity: Towards Unsupervised Continual Learning
                - Unsupervised Continual Learning via Self-Adaptive Deep Clustering Approach
                - Self-organizing neurons: toward brain-inspired unsupervised learning
                - Unsupervised Progressive Learning and the STAM Architecture
                - Continual Unsupervised Representation Learning
                - Unsupervised Continual Learning in Streaming Environments
                - Unsupervised Learning of Foreground Object Segmentation
                - Novelty detection for unsupervised continual learning in image sequences
                - Online RBM: Growing Restricted Boltzmann Machine on the fly for unsupervised representation
                - Deep Bayesian Unsupervised Lifelong Learning
            - Possibly relevant:
                - THE NEXT BIG THING(S) IN UNSUPERVISED MACHINE LEARNING: FIVE LESSONS FROM INFANT LEARNING
                - SOINN+, a Self-Organizing Incremental Neural Network for Unsupervised Learning from Noisy Data Streams
                - META-GMVAE: MIXTURE OF GAUSSIAN VAES FOR UNSUPERVISED META-LEARNING
                - Synaptic plasticity in an artificial Hebbian network exhibiting continuous, unsupervised, rapid learning
            - Not so relevant, but check again:
                - Few-Shot Unsupervised Continual Learning through Meta-Examples
                - Energy-efficient continual learning in hybrid supervised-unsupervised neural networks with PCM synapses
- Paper from auto-alert (check further):
    - https://arxiv.org/pdf/2203.13381.pdf
    - https://arxiv.org/pdf/2204.05462.pdf

Innovations / Extensions

- UCL + attention:
    - Attention in the form of pre-trained target detection.
    - Attention learnt from a target classification task.
    - Attention learnt in an unsupervised manner.
    - Attention evolved for the UCL task.

AI4Earth UCL Prototype - Experimental Variation 1 - SOTA UCL

Philosophy

- Simplicity.
- Minimalism.
- Helping. Usefulness.
- No exploration. “Million dollar experiment(s)”.

Notes

- The AI4Earth prototype can be based on a strong UCL SOTA model, combined with a strong quality estimation (QE) SOTA model. This simple combination can provide a simple, effective, robust, and extensible form of auto-curation.
- These baselines can be customized, tweaked, extended, and innovated further, in order to attempt to improve performance. For example, an obvious extension to a basic UCL algorithm is to give it some form of hierarchical semantics, e.g.: two images might be different at the species level, but might be the same at the genus (etc.) level. Can we extend UCL algorithms to take this into consideration? The iNaturalist dataset is probably ideal for testing this kind of extension.

Baselines

- GSS ["unsupervised continual learning"] → 51 results. Search complete.
- [baselines] Selected approaches [aggressive filtering was used; may have missed some relevant papers that should be cited in “related works”]:
    - Continual Unsupervised Representation Learning
        - https://proceedings.neurips.cc/paper/2019/file/861578d797aeb0634f77aff3f488cca2-Paper.pdf
        - [code available] Code: https://github.com/deepmind/deepmind-research/
    - Unsupervised Continual Learning in Streaming Environments
        - https://arxiv.org/pdf/2109.09282.pdf
        - [code available] https://drive.google.com/drive/u/0/folders/1UZ5M-LVmi859l68zRAhKdXj-R5kIfyOG
    - Unsupervised Continual Learning via Self-Adaptive Deep Clustering Approach
        - [not 100% relevant] This approach is not 100% relevant since it assumes labeled samples in the first batch of each episode: “The access of true class labels are only provided for the initial batch of each task …”
        - https://arxiv.org/pdf/2106.14563.pdf
        - [code available] https://github.com/ContinualAL/KIERA

    - Online Unsupervised Learning of Visual Representations and Categories
        - https://arxiv.org/pdf/2109.05675.pdf
        - [code will become available] GitHib code: https://github.com/renmengye/online-unsup-proto-net. As of 14/02/22 the repository is empty, however Mengye has mentioned that the repository will have code as soon as the corresponding paper has been accepted for publication.
    - Unsupervised Continual Learning Via Pseudo Labels
        - https://arxiv.org/pdf/2104.07164.pdf
        - [not sure about the code] Code: as of 14/02/22 the code does not seem to be available.
    - RETHINKING THE REPRESENTATIONAL CONTINUITY: TOWARDS UNSUPERVISED CONTINUAL LEARNING
        - https://arxiv.org/pdf/2110.06976.pdf
        - [not sure about the code] Code: as of 14/02/22 the code does not yet seem to be available, however I need to double check again.
    - Self-supervised continual learning for object recognition in image sequences
        - Paper: https://hal.archives-ouvertes.fr/hal-03465149/document
        - [not sure about the code] Code: not available?
    - Deep matrix factorization with knowledge transfer for lifelong clustering and semi-supervised clustering
        - Paper: here.
        - [not sure about the code] Code: not available?
- [supporting libraries, etc.]
    - solo-learn: A Library of Self-supervised Methods for Visual Representation Learning
        - https://arxiv.org/pdf/2108.01775.pdf
        - [code available] https://github.com/vturrisi/solo-learn
- Other papers for related works:
    - Novelty detection for unsupervised continual learning in image sequences
    - SPeCiaL: Self-Supervised Pretraining for Continual Learning
    - Generalising via Meta-Examples for Continual Learning in the Wild
    - The CLEAR Benchmark: Continual LEArning on Real-World Imagery
    - A neuro-inspired architecture for unsupervised continual learning based on online clustering and hierarchical predictive coding
    - ORDisCo: Effective and Efficient Usage of Incremental Unlabeled Data for Semi-Supervised Continual Learning
    - Avalanche: an End-to-End Library for Continual Learning
    - UNSUPERVISED CLASS-INCREMENTAL LEARNING THROUGH CONFUSION
    - Online Continual Learning Via Candidates Voting
    - Complementary Calibration: Boosting General Continual Learning with Collaborative Distillation and Self-Supervision
    - Recent Advances of Continual Learning in Computer Vision: An Overview
    - Online Continual Learning For Visual Food Classification

    - A Temporal Neural Network Architecture for Online Learning
    - Self-supervised continual learning:
        - Self-Supervised Models are Continual Learners
        - Continually Learning Self-Supervised Representations with Projected Functional Regularization
- Other papers that probably don't belong in the related works section, but which could be useful:
    - MEMORY REPLAY WITH DATA COMPRESSION FOR CONTINUAL LEARNING

Research Questions

- **RQ1.** How do SOTA UCL methods perform in a biodiversity image auto-curation setting?
- **RQ2**. How does standard UL in an episodic framework with simple cluster alignment between episodes perform in a UCL setting, compared to one or more SOTA UCL methods? [DO - 0% - Check UCL related works → is this what some UCL methods are already doing?]
- **RQx**. [DO - 0% - Continue here. Any other simple RQs?] One or more questions pertaining to potential innovations.

Experimental Design

- [DO - 0% - Complete experimental design and paper structure.]
- [Keep it simple; minimalistic]
- Experiment 1:
    - Research questions addressed: RQ1 and RQ2.
    - One large table:
        - [DO - 60% - Continue here. Flesh out the experiment completely.]
        - Rows:
            - (required) (strong baselines) UCL strong baseline conditions (one or more algorithms) (e.g. Ren et al., 2021) [DO - 50% - Continue here. Decide on which algorithms to include.],
            - (required) (strong baseline) UL on the whole dataset (no episodes and no continual learning) (one algorithm),
                - Example recent approach: [SCAN: Learning to Classify Images without Labels]() with [code here](). [DO - 0% - Check: any more recent approaches building on this work? Check in-citations.]
                - Example approach: deep feature learning followed by a simple k-means → I believe a similar approach is used in Huang el 2020, which I believe roughly conforms to the "joining clustering" approach.
            - (required) (weak baseline) UL in successive episodes but without any "alignment/adjustment steps" between successive episodes (weak baseline; catastrophic forgetting is likely to be significant).

            - Use the same UL baseline used above.
        - (required) (proposal) UL + “alignment/adjustment steps” (e.g. “cluster alignment”) between episodes. Perform UL in medium/long episodes and align clusters (etc.) between successive episodes via similarity estimation in order to cater for continual learning. Note that the meaning of “alignment/adjustment steps” might actually vary depending on the nature of the chosen UL approach.
            - Use the same UL baseline used above.
        - (optional) UCL innovation conditions, e.g.:
            - The best UCL + (attention and/or specimen detection),
            - The best UCL + self-supervision,
            - The best UCL + observation segmentation (observation boundary detection).
    - Columns:
        - Datasets:
            - (required) auto-curation of biodiversity photographs (moving/dynamic camera);
            - (required) auto-curation of camera trap frames (static camera);
            - (optional) standard datasets for UCL (e.g. MNIST, CIFAR10, CIFAR100, Omniglot).
    - Performance metrics:
        - Use the standard metrics adopted in the latest SOTA UCL papers.

Paper Structure

- Introduction.
    - Motivation - camera trap data; human bottleneck; need automation.
    - Challenges with automation: (1) multiple aspects/components, (2) huge number of classes, (3) unknown classes, (4) shifting distributions, (5) class imbalance, (6) quality variations, (7) poor lighting, (8) etc.
    - Brief introduction to UCL. UC. CL. UCL. Allow for specimens to be grouped together, when a proportion of the specimens are likely to be unknown (to science and/or to the region and/or to pre-trained DL models, etc.).
    - Why UCL is useful --> in most cases it can deal with problems 2, 3, 4, 5, etc. out of the box. Can one assume a DL solution that can recognize every single species? Right now iNaturalist can recognize how many? How fast is the model coverage growing? Can one expect it to grow to 8 million that soon. Can such a model be practical? The model is also geographically biased (e.g. North American species). Therefore it is very convenient to have a solution that can be placed anywhere, and that can cluster observations in useful ways, in a continual way, without prior knowledge of species.

    - Gaps. UCL is coming up now, but it is still early days. Significant improvements are waiting. Moreover, UCL has not been systematically applied to camera trap data to the best of our knowledge.
    - Research questions.
    - Main contributions of the paper. We propose to compare several recent SOTA UCL approaches in the context of biodiversity related image sequences. We aim to compare, and demonstrate strengths and weaknesses of different approaches. We also aim to compare UCL with UL adapted in simple ways to continual learning (CL). The paper serves as a proof-of-concept of UCL in the biodiversity auto-curation domain, and provides insights regarding which approaches work best, and also provides some potential insights on how to improve the approach further.
    - Structure of paper.
- Related works.
    - (mandatory) Auto-curation.
    - (optional) UL.
    - (optional) CL.
    - (mandatory) UCL.
- Methods.
    - Methods used, e.g. UCL1, UCL2, etc.
    - Datasets.
    - Experimental design. Experiment 1, etc.
    - Evaluation metrics.
- Results.
    - Tables of results. Figures?
- Discussion.
    - Interpretation of results.
    - Were the RQs answered? Is UCL viable in the domain of the auto-curation of biodiversity image sequences (i.e. static camera traps and human biodiversity photographers).
    - Strengths and weaknesses of approaches?
    - New questions.
    - Suggested ways forward (short/medium term).
    - Future work (more long term)

AI4Earth UCL Prototype - Experimental Variation 2 - From UL to CL

General Notes

- Experimental variation 2 is arguably a bit simpler than experimental variation 1.

- Main goal: to demonstrate that unsupervised learning is viable as an approach for observation segmentation and that it has potential for continual learning in the domain of biodiversity data auto-curation.
- Two main functions of UL in this context: (1) observation segmentation, (2) grouping of similar species, specimens, groups together for easier post-auto-processing labelling by humans. Regarding the second point, all specimens of the same species will be grouped together, regardless of when they were recorded, so that humans can conveniently label them in one go. The usefulness of this latter function might become more apparent when one considers multiple cameras that might have been recording for 1 year in a remote location, before receiving human attention (for labelling and/or detection of new species).
- Think about distance measures based on auto-encoder bottleneck representations (e.g. train an autoencoder on the data; use simple distance metrics on bottleneck representations).

Assumptions

- We assume that images/frames contain one target specimen, or if they contain multiple specimens that the algorithm will focus only on the more prominent one. Future work can extend the research/solution such that multiple specimens in the same frame can be explicitly considered (e.g. the clustering is performed on the contents of one or more bounding boxes (per frame) corresponding to specimen detections).

UL properties

- The following properties are generally important in the auto-curation domain and should be checked carefully in each paper:
    - Adaptive cluster numbers.
    - Adaptive similarity metrics.
    - Adaptive cluster shapes.
    - Explicit novelty detection.
    - Continual learning.
    - Efficient consolidative supervised learning of pseudo-labels (e.g. rather than storing thousands of prototypes, training a network to classify images directly into clusters). How does this combine with the ability to adapt clusters continually? How else can we address the cost of a prototype-based approach?
    - Hierarchical clustering (e.g. same specimen from different perspectives (e.g. top vs. bottom of an insect).
    - [DO - 0% - Any other useful properties?]

Research Questions

- [DO - 0% - Check and refine all.]

- RQ1. Can basic (out of the box) UL methods perform more than half-way between chance-level and supervised level performance, in terms of observation segmentation in a non-CL setting?
- RQ2. Can simple modifications to the basic UL methods improve performance noticeably, in terms of observation segmentation in a non-CL setting? Modifications can be considered from different perspectives, e.g.: neural architecture, learning algorithm, training protocol, pre-processing, data (e.g. absence/presence of time stamps).
    - RQ2.1. Does the addition of time-stamps in a simplistic manner lead to accuracy improvements?
    - RQ2.2. [DO - 0% - Include at least 2 additional sub-questions.]
- RQ3. How do the best versions of UL from experiments targeting RQ2 perform in terms of clustering accuracy (i.e. species x is grouped with species x) in a non-CL setting?
- RQ4. How do the best versions of UL from experiments targeting RQ2 perform in terms of clustering accuracy (i.e. species x is grouped with species x) in a CL setting?
- RQ5. Can clustering accuracy in a CL setting based on the best methods from RQ2 be improved via simple CL-based modifications and/or modifications inspired by current UCL SOTA methods?

Literature

Unsupervised learning approaches

- Some notes:
    - The GSS [intitle:adaptive intitle:"k-means" clustering (intitle:review OR intitle:survey OR intitle:overview)] yields 0 results. Have no surveys on the adaptive versions of k-means been written? Check further. This could be an open problem and opportunity, e.g.: (1) a review on adaptive versions of k-means, (2) an experimental comparison of adaptive versions of k-means with or without some innovations.
- Some queries:
    - GSS [(intitle:review OR intitle:survey OR intitle:overview) "unsupervised learning" clustering neural ("image clustering" OR "image clusters") clustering] → 180 results.
    - GSS [similarity (intitle:review OR intitle:survey OR intitle:overview) "unsupervised learning" clustering ("neural networks" OR "deep learning") ("image clustering" OR "image clusters") clustering] → 148 results
    - GSS [(intitle:review OR intitle:survey OR intitle:overview) (intitle:clustering OR intitle:"unsupervised learning") ("deep learning" OR "neural networks")] → 576 results
- Features to search for in the papers:
    - Name of algorithm.
    - Example paper mentioning the algorithm. [the papers below]
    - [optional] First/primary source of the algorithm.
    - [optional] When was the algorithm first proposed?

    - Is the number of clusters adaptive?
    - Is similarity estimation learnt?
    - Is there explicit novelty detection?
    - Does the solution explicitly cater for continual learning?
    - Is code available?
- Some papers to check:
    - https://ieeexplore.ieee.org/document/9517087
    - https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=8412085
    - https://www.net.in.tum.de/fileadmin/TUM/NET/NET-2020-04-1/NET-2020-04-1_08.pdf
    - https://openaccess.thecvf.com/content/CVPR2021/papers/Park_Improving_Unsupervised_Image_Clustering_With_Robust_Learning_CVPR_2021_paper.pdf
    - https://ieeexplore.ieee.org/document/8296309
    - https://www.ire.pw.edu.pl/~arturp/Dydaktyka/PPO/pomoce/clustering.pdf
    - A survey on image data analysis through clustering techniques for real world applications
    - https://link.springer.com/chapter/10.1007/978-3-030-49666-1_2
    - https://aip.scitation.org/doi/abs/10.1063/5.0017774
    - https://link.springer.com/article/10.1007/s10462-020-09913-7
    - http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.225.5050&rep=rep1&type=pdf#page=48

Experimental Design - Experiments

- [DO - add these soon.]

Key steps

- Label all TreeAnt data for observation segmentation. Create a dataset that can potentially be shared. Use convenient representations and data formats.
- Train one or more decent models on the observation segmentation dataset. Keep track of all OS performance results.
- Briefly research basic UL methods appropriate for experimentation.
- Implement and/or re-use one or more UL methods.
- [addressing RQ1] Apply the UL methods to the TreeAnt data. Record all OS performance metrics.
- [addressing RQ2] Modify these simple UL methods and record OS performance.
- [addressing RQ3] Select the best OS UL approach and compute clustering accuracy.
- [addressing RQ4] Apply the best OS UL approach to a CL setting. Compute OS and clustering accuracy.
- [addressing RQ5] Modify the best OS UL approach in order to improve CL performance. Compute OS and clustering accuracy.

References

- Huang, J., Dong, Q., Gong, S. and Zhu, X., 2020, April. Unsupervised deep learning via affinity diffusion. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 34, No. 07, pp. 11029-11036).
- Min, E., Guo, X., Liu, Q., Zhang, G., Cui, J. and Long, J., 2018. A survey of clustering with deep learning: From the perspective of network architecture. IEEE Access, 6, pp.39501-39514.
- Ren, M., Scott, T.R., Iuzzolino, M.L., Mozer, M.C. and Zemel, R., 2021. Online Unsupervised Learning of Visual Representations and Categories. arXiv preprint arXiv:2109.05675.
- Yang, B., Fu, X., Sidiropoulos, N.D. and Hong, M., 2017, July. Towards k-means-friendly spaces: Simultaneous deep learning and clustering. In international conference on machine learning (pp. 3861-3870). PMLR.