Open-world Machine Learning: Supplementary Material

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This file is created as supplementary material for the "Open-world Machine Learning: Applications, Challenges, and Opportunities" review paper. In this file, the first part discusses the benchmark datasets used in open-world learning. It also lists all datasets based on the proposed year and provides the links for publicly available datasets. The next part discusses related areas such as Transfer Learning, Active Learning, Lifelong Machine Learning and Multi-Task Learning

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1 Datasets Used in Open-world Machine Learning

Most of the researchers utilised benchmark datasets to evaluate the performance of their proposed algorithms. Some researchers built their datasets or altered the existing dataset and evaluated the methods. In this section, we discuss some of the datasets primarily and frequently used in both the domain of open-world machine learning.

Figure 1 shows the classification of datasets for CVIP and NLP with their proposed years. Next, we discussed publicly available datasets that are used in OWML.

Caltech-256 [17]: $caltech - 256$ has a set of 256 categories of objects and a total of 30607 images in this dataset. Each category contains a minimum of 80 and a maximum of 827 images; these categories are further labelled with three tags based on image quality. The labels are *good*, *bad*, and *none* (out of the category). The *good* indicates clear vision, and the *bad* indicates clutters or artistic examples where *none* indicates the image does not belong to the particular category.

MNIST [26, 27]: Modified National Institute of Standard and Technology, wildly known as *MNIST* is a handwriting dataset. It is a modified version of NIST. MNIST is used in optical character reorganization and is also used as a test case in pattern recognition and machine learning. We have analyzed that MNIST has become a standard for testing machine learning algorithms. There are 60000 training images; some may use for validation and 10000 images for testing purposes. All the digits are black and white and normalized in seize, the center intensity with $28 * 28$ pixels; thus, the dimension of the image is $28 * 28 = 784$, and each element is a binary. The MNIST has tested for almost all the benchmark baseline algorithms and well-known Fields of classification such as

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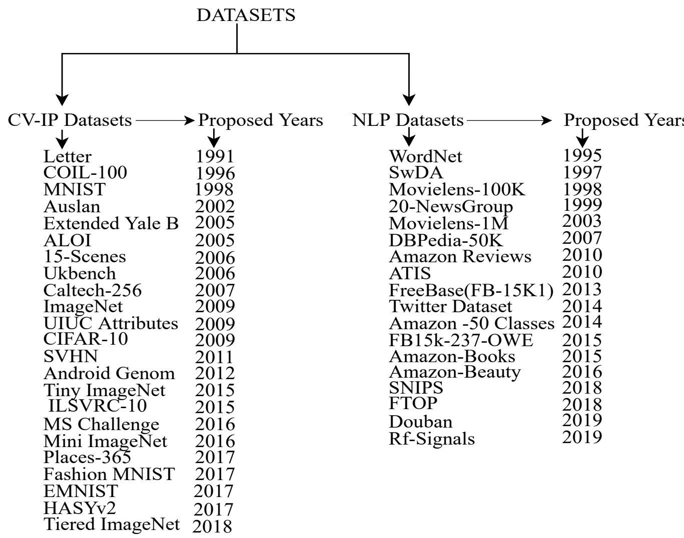

Fig. 1. Classification of Datasets Used in CV-IP and NLP with Proposed Years

linear classification, convolution neural networks, simple neural networks, K-Nearest neighbours, support vector machines (SVMs), boosted stamps, and nonlinear classification.

Fashion-MNIST [54]: The Fashion-MNIST is a dataset of Zalando's article images containing a training set of 60,000 images and a test set of 10, 000 images. Each image is a 28x28 pixel and grayscale image related to a label from 10 different classes. Zalando aims for Fashion-MNIST to serve as a substitution for the original MNIST dataset, which comprises many handwritten digits, for benchmarking artificial intelligence and machine learning algorithms.

ImageNet [14]: *ImageNet* is a large-scale ontological dataset of visual objects. The structure of ImageNet inspired by WordNet datasets; thus, it constructs the backbone of WordNe. ImageNet has 80000 synsets of WordNet with around 1000 full resolution cleaned images and its updating continuously. The basic ImageNet contains 3.2 million images with 12 sub-trees and 5247 synsets. ImageNet is a hierarchical dataset like WordNet, which contains the synonym's of the world in a tree structure. The 12 sub-trees consist of the following categories: bird, reptile, vehicles, musical instruments, tools, fruits, mammals, fish, amphibians, geological formulations, furniture, and flower with 5247 synsets. This data is continually updated at 50 million images in a hierarchical structure. The evolution with various baseline methods showed that the ImageNet have a 99.7% average precision rate.

Tiny-ImageNet [25]: Tiny-ImageNet is a collection of 100000 images that are retrieved from the internet. The resolution of all these images is $32 * 32$ pixels and $64 * 64$. Tiny-ImageNet has 200 categories of images, of which 100, 000 images for training, 10000 for validation, and 10000 images are reserved for testing. Images are collected by sending all search words in WordNet to the image in the search engine. it is a successful dataset tested on application-specific algorithms because of a high level of noise and low resolution. Tiny-ImageNet is suitable for general-purpose algorithms. It also contains synsets of high quality with an average resolution of $400 * 350$.

CIFAR-10 [21]: The Canadian Institute for Advanced Research developed the CIFAR-10 data set. It contains ten categories (dog, frog, automobile, bird, horse, ship, truck, aeroplane, cat, and deer) of images, as it is a subset of CIFAR-100, consisting of 100 categories.A total of 60000 colour images are in CIFAR-10 with resolutions of $32 * 32$ pixels, and every class has 600 images. The dataset is divided into training and test sets of 50000 and 10000 images respectively. The entire dataset is divided into batches, five batches for training and one for testing. The testing batch has 1000 random images, and the rest of the images are randomly contained by training batches.

SVHN [36]: The Street View House Number (SVHN) contains 600000 labelled digits that are cropped from actual street view images. The initial goal of this dataset is to identify house numbers from original street view images. There are two types of images one is whole numbers, and another is cropped digits. The whole numbers contain high-resolution full-size original images with character-level bounding boxes for the house number. The cropped digits are character-level ground truth, and all these digits are resized with a resolution of $32 * 32$ pixels. The SVHN is further divided into training and testing, and there are 73257 digits images for training and 26032 digits for testing. The rest of the images are also reserved as extra for training.

20-NewsGroup [23, 40]: It is a collection of near about 20000 new documents, which are collected from different newsgroups. It is one of the most popular datasets for the application that is based on text classification in machine learning. All the newsgroups are different, but some new groups are related to each other. Generally, 90% of documents are used for training and 10% for testing. 20-NewsGroup is publicly available in different forms, and the original dataset is not sorted but later on is sorted by date. The headers and duplicate data are also removed in this version. The latest data version has 18828 documents with only "From" and "Subject" headers.

Amazon Product Reviews [35]: Amazon.com has been one of the most successful e-commerce websites globally since it emerged. The amazon product review dataset contains 5.8 million reviews written by 2.14 million for 6.7 million products from 9600 different categories when extracted from these reviews. The dataset has eight different headers: Product ID, Reviewer ID, Rating, Date, Review Title, Review Body, Number of Helpful Feedback, and Number of Feedback. It can be used for feature identification and construction of both reviewers and reviews, and the features can be Review Centric or Product-Centric. The amazon product reviews.

50-Class Reviews [9]: The 50-Class review dataset is a collection of reviews with 50 different categories of products. The data set has two versions, one has reviews of 50 different electronic items, and the other has 50 different non-electronic items. There are 1000 reviews for each product or domain.

WordNet [34]: WordNet is a multi-language (Approx 200 languages) lexical dataset of semantic relationships among words, including meronyms, synonyms, and hyponyms. Some synsets contain synonyms in a group with short definitions and examples. The WordNet is a popular dataset for text analysis applications in artificial intelligence and machine learning. Initially, it was created for the English language; later, it extended to other languages, and updating is continuous to add a new language to WordNet. The WordNet contains approx 175979 words which are organized in 175979 synsets, and there are 207016 pairs which are word-sense pairs. All synsets are connected with semantic relations.

SwDa [19, 43, 46]: The Switchboard Dialog Act Corpus (SwDA) covers the SwDA-1 Telephone Speech Corpus, and some tags recapitulate semantic, syntactic, and pragmatic information about the related turn.

Some publicly available datasets with their repository link are shown in Table 1.

2 Related Areas

Some related areas closely associated with open-world machine learning are mentioned and discussed briefly in this section.

Table 1. Publicly Available Benchmark Datasets

Dataset	Link
Caltech-256 [17]	http://www.vision.caltech.edu/Image_Datasets/Caltech256
MNIST [26, 27]	http://yann.lecun.com/exdb/mnist
Extended Yale B [28]	http://vision.ucsd.edu/ leekc/ExtYaleDatabase/ExtYaleB.html
ALOI [16]	https://aloi.science.uva.nl
UIUC Attributes [15]	https://vision.cs.uiuc.edu/attributes
Mini ImageNet [53]	https://cseweb.ucsd.edu/ weijian/static/datasets/mini-ImageNet
Fashion-MNIST [54]	https://github.com/zalandoresearch/fashion-mnist/tree/master/data
HASYv2 [48]	https://zenodo.org/record/259444#.YX94vBzhXIU
ImageNet [14]	http://image-net.org/download
Tiny-ImageNet [25]	http://cs231n.stanford.edu/tiny-imagenet-200.zip
CIFAR-10 [21]	https://www.cs.toronto.edu/~kriz/cifar.html
RF Signal Dataset [18]	https://github.com/xguo7/MDCC-for-open-world-recognition
Twitter Dataset [39]	https://github.com/xguo7/MDCC-for-open-world-recognition
SVHN [36]	http://ufldl.stanford.edu/housenumbers
20-NewsGroup [23, 40]	http://qwone.com/~jason/20Newsgroups
Amazon Product Reviews [35]	https://jmcauley.ucsd.edu/data/amazon
WordNet [34]	https://wordnet.princeton.edu/download
SwDa [19, 43, 46]	https://web.stanford.edu/~jurafsky/ws97/
ATIS [52]	https://rasa.com/docs/rasa/nlu-training-data/#json-format
FB15k [5]	https://www.microsoft.com/en-us/download/ confirmation.aspx?id=52312
DBpedia [3]	https://wiki.dbpedia.org/datasets
EMNIST [11]	https://www.nist.gov/itl/products-and-services/emnist-dataset
Auslan [20]	https://archive.ics.uci.edu/ml/datasets/Australian +Sign+Language+signs+(High+Quality)
Ukbench [37]	https://archive.org/download/ukbench
Places-2 [56]	http://places2.csail.mit.edu/download.html

2.1 Transfer Learning

Traditional Machine Learning (ML) techniques predict the expected data by applying analytical principles trained on previously accumulated unlabeled or labelled training examples [4, 22, 55]. Analysis of transfer learning has brought attention since 1995 in several titles: knowledge transfer, learning to learn, multitask learning, knowledge consolidation, inductive transfer, knowledge-based inductive bias, context-sensitive learning, cumulative learning [49, 51], and multitask learning framework [31]. Transfer learning involves interpreting data for a reference task to provide a productive basis for a new task. Transfer learning is often applied to specific data sets with some labelled value. For example, an actual demonstrative prototype of one virus would have a significant advantage in developing a distinguishing prototype for another virus, for which fewer training samples are available. While all learning involves generalization across all queries, transfer learning illustrates the transfer of information across comparable but non-consistent fields, tasks, and distributions. In distinction, the unlabeled data does not require to be obtained from a similar task in the transfer learning framework. In the prior decade, there has been substantial development in improving cross-task transfer by utilizing both discriminative and generative strategies in a broad category of frames.

2.2 Active Learning

Active Learning [50] is a discipline of machine learning where the algorithm is designed for learning and can choose the data for learning or learning strategy generated during learning (Figure 2). The active learning methodologies can play an essential role in domains that deal with real-time data such as speech recognition, information extraction [42], classification, and filtering. Moreover, active learning provides high accuracy with a small testing size of labelled data.

There are different types of scenarios of active learning, such as membership query synthesis [1], stream-based selective sampling [12], and pool-based active learning [29]. The standard data mining methods learn models with isolated data and make a prediction based on static models [4,

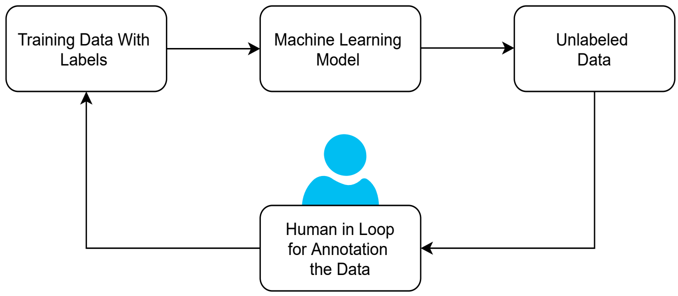

Fig. 2. Basic Framework of Active Learning [41]

22, 55]. It needs to use previous knowledge, or a learning model should transfer knowledge and be used to predict future learning. It is termed transfer learning [38]. The knowledge can be transferred in various forms such as transferring knowledge of instances [13], knowledge of feature representations [2] (for both supervised and unsupervised), knowledge of parameters [24] and relational knowledge [33].

2.3 Lifelong Learning/Continual Machine Learning

Lifelong machine learning is a system that can continuously learn from different domains, and this knowledge can be used effectively on future tasks in an efficient manner [45]. The selective knowledge is transferred when learning a novel task. Knowledge is retained from a different source and improves learning. The various techniques of lifelong learning as prior work in knowledge retention improves learning a new task. The significant tasks of lifelong machine learning are shown in Figure 3.

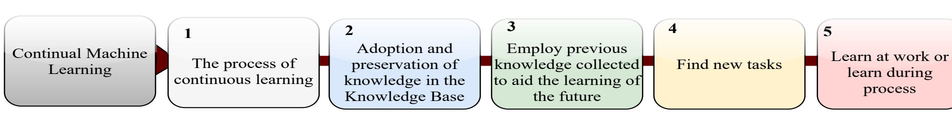

Fig. 3. Tasks of Continual Machine Learning

There are different names: constructive induction, incremental and continual learning, explanation-based learning, sequential task learning, and never-ending learning. These methods are further divided into different categories: lifelong machine learning is supervised learning, continual learning is reinforcement learning, and self-taught learning or never-ending learning is unsupervised learning.

Supervised lifelong learning uses an explanation-based Neural Network (EBNN) with a back propagation gradient. Whenever new learning tasks occur, EBNN utilises prior domain information of the task. EBNN gives more accurate outcomes even with fewer amounts of data. In [44], authors suggested knowledge-based cascade correlation neural networks. This method utilises prior trained networks and concealed units to set the new bias for a novel task. Unsupervised Lifelong learning is used to increase the system's scalability, and adaptive resonance theory has been used to map the bottom and top nodes of clusters. It uses a threshold for a new example node, a map with an attention parameter (below threshold).

In [47], authors proposed a novel approach to ensemble clusters from the primary partition of objects; it uses labels of the cluster deprived of accessing the original features. The self-taught learning models build high-level features using unlabeled data and test such models for various

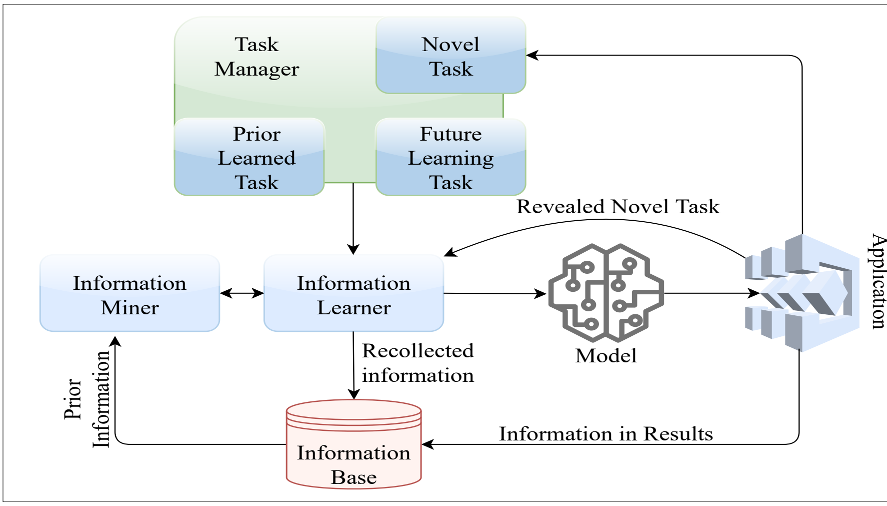

Fig. 4. Basic Framework of Lifelong Machine Learning [10]

image, web, and song genre classification applications. Lifelong learning goals can be achieved by another popular method: Never-ending Language Learner (NELL) [6]. NELL extracts data or reads information from the web and increases its knowledge, then learns how to perform a new task better than the same task done the earlier day. Rather than focus on traditional machine learning, the system should retain knowledge and transfer this to the system as the learning agent. The system should learn sequential tasks and increase their magnitude.

2.3.1 Challenges and Benefits of Lifelong Learning Models [45].

- **Input /output Type, Complexity and Cardinality:** The real-time environment has a variety of data from different domains; it can differ in nature. The attributes of each input may vary according to their source and required task.
- **Training Examples Vs Prior Knowledge :** In life-long learning systems, prior knowledge is a crucial part of the end-to-end system to achieve accuracy while performing a new task. There is a need to retain valid data from the knowledge base that must have information deception as a training example.
- **Effective and Efficient knowledge Retention:** The system must retain efficient information that must not be erroneous. Furthermore, it must use finite memory to store knowledge with limited computational capacity. The system must be capable of handling duplicate data and increasing the accuracy of prior knowledge.
- **Effective and Efficient knowledge Transfer :** Prior knowledge should not increase computational time and effort. Moreover, the knowledge transfer does not generate less accurate inputs/models for new tasks. There are three major components of lifelong learning.
  (1) Retention of learned task knowledge,
  (2) Selective transfer of prior while learning a new task, and
  (3) The system must ensure that retention and transfer of knowledge must be efficient.
- **Scalability:** Scalability is one of the most challenging and essential aspects of almost all fields of computer science. The system must be able to adapt increments in volumes of input data. The lifelong learning systems must be able to address the space and time complexity of all these factors.

- **Heterogeneous Domain of Task:**The lifelong learning systems must handle data from different domains by establishing relations between the origin and targeted domains. There are many standard features, but diversity in transferred knowledge data also exists. The system must have the ability to map features in transferred knowledge.

2.4 Multi-task Learning

Multi-task learning (MTL) [7, 8, 30] acquires various associated tasks concurrently, beaming at delivering a more reliable representation by using the associated knowledge yielded by various jobs. Introducing inductive bias in Multi-task learning is to create a joint hypothesis space for every job by utilizing the task-relatedness building. It inhibits over-fitting in the specific job and therefore has a more immeasurable generalization capability. Unlike transfer learning, it mainly does various jobs preferably than various areas as much of the area's existing research is based on several comparable jobs of the identical application area. Multi-task learning allows those jobs are strictly associated with each other. There are several hypotheses regarding job-relatedness, which drive another modelling strategy. Many researchers hypothesize that all job data come from the same sources and correlate to the standard or global models. According to this hypothesis, they created the association among jobs employing a task-coupling parameter, including regularization.

In [32], authors proposed multi-task learning for the deep neural network. They classify multi-tasking tasks into two categories for deep learning. The first is classification, and the second is ranking; in classification, the model identifies the queried domain, whereas the ranking model finds the relevant queries.

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