Robust Identification of EV Charging Profiles

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***Abstract*—Electric Vehicle (EV) charging profiles are important for electric energy distribution network operation, load forecasting, as well as utility grid expansion and planning. A typical individual EV charging profile typically includes its start time, its initial battery state-of-charge (SOC), and its (total) charging time. For distribution networks, a network/regional EV charging profile also includes number of EVs at different times (e.g., each hour) of the day. Most existing work on EV charging profiles assume that EV charging profiles follow certain statistical distributions in a universal manner. However, EV charging profiles are highly related to weather conditions, traffic patterns, rate tariffs, population density growth, and population active time periods, for which different regions (residential vs commercial, rural vs suburban, and developed vs developing) are fundamentally different. Instead of make simplification, this paper proposes to extend authors work on non-intrusive load modeling, utilize ubiquitous advanced metering infrastructure (AMI) data such as smart meters, and build robust and accurate EV charging profiles for any networks under consideration.**

I. Introduction

U.S. Department of Energy (DOE) forecasts that by 2050 there will be over 2.3 million new light-duty EVs and hybrid vehicles sales per year [1], as shown in Figure 1. Deployment of high volume of EVs has tremendous amount of impact on societal-scale infrastructures in terms of reducing dependency on imported energy, alleviating environmental concerns, enhancing sustainable development, reshaping domestic manufacturing, and incorporating intelligence into the Smart City framework. At the request of Congress, National Research Council (NRC) has investigated key barriers and issues related to deployment of high volume of EVs [2]. NRCs final report has identified three issues that "are of particular importance": 1) vehicle cost and federal incentives, 2) batteries cost and performance, and 3) new public charging infrastructure.

This paper aims at contributing to the third issue, i.e., technical challenges related to new and upgraded charging infrastructures, including distribution networks, to meet the need by high penetration of EVs. For instance, In 2016, the average annual electricity consumption for a U.S. residential utility customer was 897 kWh per month [3]. However, a residential level 2 EV charger is between 3.4kW and 19.2kW with typical 6.7kW. In other words, average household electricity consumption per month could be double with future charging infrastructures. A large portion of current aging infrastructure will not be able to support wide range of EV charging at residential homes. In order for utilities to upgrade their infrastructure, a tremendous amount of investment is needed. Therefore, a reliable and applicable method is desired to determine which households are currently using charging infrastructure and how much they consume. Furthermore, wide deployment of EVs charging infrastructures will induce tremendous impact on the electric power distribution network, including voltage profile [4], power quality [5], critical components such as transformers [6], energy loss [7], and required system upgrades by utilities [8].

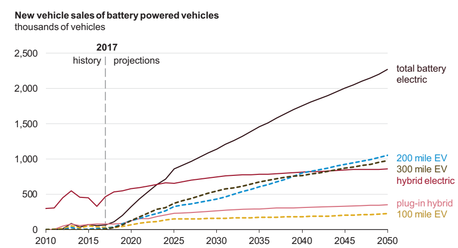

Fig. 1. Projection of EV and Hybrid Vehicles Sales by 2050 [1].

EV charging profiles (starting time, charging period, and initial SOC) typically vary significantly between residential and commercial areas, between rural and urban areas, and also between developed and developing areas. An accurate load profile including large deployment of EVs is critical for 1) infrastructure expansion planning; 2) system response and stability with respect to load and traffic disturbances; 3) load forecasting and economic system operation; and 4) abnormal events detection to prevent cascading outages. Figure 2 shows the daily load profiles of August 2016 and September 2016 for the City of Philadelphia. We can observe that

- In August 2016, early morning demand started to drop between 4am and 5am, while in September 2016 early morning demand started to drop between 7am to 8 am. In other words, people stayed on average 2-3 more hours at home in morning in September 2016.
- In August 2016, late afternoon demand started to pick up around 8pm with daily peak between 9pm and 10pm, while in September 2016 late afternoon demand started to pick up around 6pm with daily peak around 9 pm. In other words, people arrived home 1-2 hours earlier in September.

To summarize, with high penetration of EVs, their charging profiles are highly related to season, weather, traffic, and many other factors. Furthermore, when and how long EVs are charging will have a significant impact on load profiles as well as power system operation.

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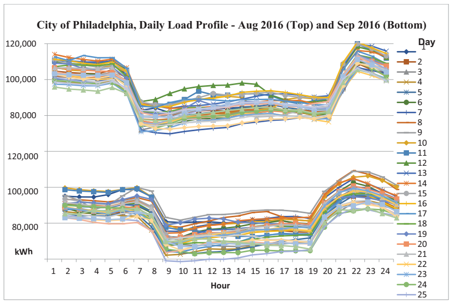

Fig. 2. City of Philadelphia daily load profiles - Aug and Sep of 2016.

In literature, assumptions and simplification have been made on EV charging profiles. To list but a few due to space limit, Reference [9] proposed that the initial SOC at the beginning of charging at UK might follow a log-normal probability density function (pdf), while starting time could be estimated by a Gaussian. It is unknown whether these results by specific UK data can be used in other regions. The charging period has been proposed by [10] to be represented by a truncated normal distribution. However, the charging starting time for a rural residential district, an urban residential district, and a commercial district cannot be the same. Moreover, the charging period has been proposed by [11] to be represented by a truncated normal distribution.

Instead of making assumptions and simplifications on EV charging profiles by parital and non-universal data, this paper proposes to utilize widely and readily available ubiquitous AMI data and Non-Intrusive Load Monitoring (NILM) approaches to extract EV charging profiles. NILM is a technique to analyze household power consumption to identify granular appliance consumption profiles. Started with its first introduction by [12] in the late 1980s, NILM has attracted wide range of attentions and interests globally. A large amount of work has been reported on electric load identification by worldwide researchers. The general framework for electric load identification contains three main modules/steps: event detection, feature extraction, and load identification using extracted features. The load identification process starts if a turn ON/OFF event is detected. Comprehensive reviews on NILM can be found in [13].

As the main contribution of this paper, authors propose that NILM can be extended to extract EV charging start time, period, initial SOC at every household. Locally, each smart meter can estimate individual EV charging profile and transmit to EMS. Estimation errors can be reduced at EMS level with long-term (several months) data from wide areas. Utilities and ISO/RTOs can use millions of individual profiles to build accurate charging profiles for any desired region.

The remaining of this paper is organized as follows. Section II discusses existing literature of NILM and energy disaggregation, while Section III proposes an EV charging profiles identification framework based on big data and deep learning. Based on Section III, Section IV discuss data pre-processing and details of the proposed framework. Section V presents experiment results, and Section VI draws the conclusions as well as future work.

II. Energy Disaggregation

One major application of NILM is *energy disaggregation*, which aims at separating individual appliance energy consumption from an aggregate electricity consumption signal. In literature, there are a large number of methods proposed for energy disaggregation. Comprehensive reviews on existing techniques can be found in [14]. From authors' view, majority of existing methods can be categorized into unsupervised learning and supervised learning. The difference between them is that the former does not require any ground truth for training.

Summarized in [15], most unsupervised learning methods are based on Factorial Hidden Markov Models (FHMM) [16]–[19], which is a probabilistic graph model to detect On/Off events of each appliance. Reference [16] proposed a Conditional Factorial Hidden Semi-Markov Model which works well for appliances with simple or modestly complex power signatures, but suffers from complex signatures. Reference [17] developed a Difference Additive Factorial Approximate MAP, which can perform exact inference and is computationally efficient. A convex formulation of approximate inference avoids susceptibility to local optima. Reference [18] presented a solution by designing a hierarchical probabilistic model, which has efficient and effective estimation of latent states. Reference [19] proposed a ensemble methods named hierarchical FHMM, which handles the correlations between devices in order to strengthen independence assumption of devices and preserve the one-at-a-time condition. Although the FHMM is a favorable model, its main constraint lies in the assumption of probabilistic distributions based on observations and is highly susceptible to local optima with a substantial number of HMMs.

Utilizing supervised learning for energy disaggregation has been attracting more attention. Sparse coding based techniques are to frame energy disaggregation as 'single-channel source separation' task. Reference [20] developed the discriminative disaggregation sparse coding algorithm with a novel discriminative training procedure and showed that the accuracy of sparse coding was improved significantly. Co-Sparse coding in [21] claimed that it requires fewer training volume and indirectly reduces sensing cost without losing disaggregation accuarcy. Another research work showed that adding the sum-to-k constraint to non-negative matrix factorization [22] can lead to considerable improvement in estimation accuracy. Reference [23] proposed a method via learning 'powerlets' and sparse coding and involving convex relaxation makes the computation more efficient. To summarize, supervised learning algorithms learn from data with ground truth and then make a determination (or prediction). For engineering problems such as energy disaggregation, understanding of available data and development of near-human-understanding level of features are critical. Most existing supervised machine learning algorithms showed good results for a certain dataset and cannot be easily extended to other datasets without significant modification or selection of parameters.

Sometimes, it is more intereseting to first learn the choice of data representation (or data features), also known as *representation learning*, i.e., learning representations of available data to find out how to better extract useful information. A special category of representation learning, known as deep learning, has been very popular recently. Deep learning algorithms are Artificial Neural Networks (ANNs) with deep layers and larger number of neurons, which can process massive amounts of data with deeper 'memory'. We claim that deep learning is a better fit for EV charging profile identification than supervised machine learning.

In this paper, we utilized the deep learning approach for identification of EV charging profiles. Reference [24] represented deep dictionary learning representation for energy disaggregation and it has good performance in accuracy. Based on great advance of deep learning application to image classification, speech recognition and so on, recent years deep learning approaches for energy disaggregation has been investigated. Compared with other supervised learning technique, one distinct advantage is that deep learning does not need handcraft the feature. Reference [25] demonstrated several deep learning architectures like Long Short-term Memory (LSTM), Denoising Autoencoders (DAEs) and Deep Neural Networks (DNNs). Reference [26] proposed a generic deep disaggregation model using a fully Convolutional Neural Network (CNN).

Once EV charging load is disaggregated from the aggregate load, start time, charging time and energy consumption can be achieved. To author's best knowledge, reference [27] is probably the only exsiting work which studied NILM for EV charging, which is based on real-world Pecan Street Dataset [28]. One major claim by [27] is that the main challenge of disaggregating an EV charging profile from household (aggregated from many appliances) power waveforms is to distinguish EV charging lumped waveforms from air conditioners (AC), as shown in Figure 3. It should be noted that an AC power signal exhibits two kinds of waveform patterns: spike trains and lumps. The authors validated this claim by cross checking other databases such as typical power waveform of household AC units (mainly an induction motor driving a compressor) from the benchmark REDD database for which the sample rate is around 1 Hz. Therefore, to distinguish and disaggregate EV charging from AC operating remains the major technical challenge for EV charging profile identification.

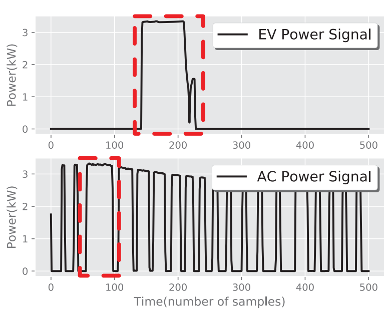

Fig. 3. An EV power signal and an AC power signal from Pecan Street dataset, which is 1/60 Hz.

The problem gets more complicated while both EV charging and AC operating are carried out at the same time. The technical challenge lies in how to determine whether an EV indeed starts charging, to distinguish from different power levels of an operating AC unit.

III. Deep Learning Architecture

This section presents a deep learning framework for EV charging profile identification, including denoising autoencoder combined with convolutional neural networks.

A. Feedforward Neural Network

Feedforward neural networks, also called multilayer perceptrons (MLPs), are the basic deep learning architecture. Given labeled training examples $(\boldsymbol{x}, \boldsymbol{y})$, the goal of a feedforward neural network is to approximate some function $\boldsymbol{y} = \boldsymbol{f}^*(\boldsymbol{x})$. A feedforward network defines a hypothesis $\boldsymbol{f}(\boldsymbol{x}, \boldsymbol{\theta})$ and learn the value of the parameters θ through fitting to our training examples so that our hypothesis can become the best function approximation $\boldsymbol{y} = \boldsymbol{f}(\boldsymbol{x}, \boldsymbol{\theta})$. With the following representation $\boldsymbol{x} \rightarrow \boldsymbol{f} \rightarrow \boldsymbol{y}$, the above models are called feedforward.

Feedfoward networks are basis for other deep learning architecture. Typically, $\boldsymbol{f}(\boldsymbol{x}, \boldsymbol{\theta})$ is composed of many different functions which are connected in a chain. The overall length of the chain gives the depth of the model. The first layer of deepforward network is called the input layer and the final layer is called the output layer. When the depth of the model is more than two, the intermediate layers are called hidden layer.

B. Undercomplete Autoencoder

An autoencoder is a neural network that is trained to copy its input to its ouput [18]. As an unsupervised learning technique, autoencoders are used for dimensionality reduction or feature learning. A linear autoencoder with a single hidden layer is almost the same as principal component analysis (PCA). But autoencoders can learn a more powerful nonlinear generalization of PCA. An autoencoder consists of two parts: encoder and decoder. For a 3-layer network, an encoder $\boldsymbol{h} = \boldsymbol{f}(\boldsymbol{x}, \boldsymbol{\theta})$ plays a role in extracting hidden representation $\boldsymbol{h}$ from our input $\boldsymbol{x}$ and a decoder $\boldsymbol{r} = \boldsymbol{g}(\boldsymbol{h}, \boldsymbol{\theta}')$ is responsible for producing a reconstruction $\boldsymbol{r}$ from the hidden representation $\boldsymbol{h}$.

Although autoencoders can not learn to copy perfectly, it always learns useful features of the data, which is what we expect to get. In order to let the code $\boldsymbol{h}$ obtain useful representation, $\boldsymbol{h}$ is constrained to have a smaller dimension than $\boldsymbol{x}$. This undercomplete representation forces the autoencoder to learn the most effective features.

The learning process is to optimize the parameters of the model to minimize the average reconstruction loss.

$$\boldsymbol{\theta}^*, \boldsymbol{\theta}'^* = \mathop{\arg\min}_{\boldsymbol{\theta}, \boldsymbol{\theta}'} \frac{1}{n} \sum_{i=1}^{n} L(\boldsymbol{x}^{(i)}, \boldsymbol{r}^{(i)}) \tag{1}$$

$$\boldsymbol{\theta}^*, \boldsymbol{\theta}'^* = \mathop{\arg\min}_{\boldsymbol{\theta}, \boldsymbol{\theta}'} \frac{1}{n} \sum_{i=1}^{n} L(\boldsymbol{x}^{(i)}, \boldsymbol{g}(\boldsymbol{f}(\boldsymbol{x}^{(i)}, \boldsymbol{\theta}^{(i)}), \boldsymbol{\theta}'^{(i)})) \tag{2}$$

where L is a loss function such as the square error $\boldsymbol{L}(\boldsymbol{x}, \boldsymbol{r}) = \|\boldsymbol{x} - \boldsymbol{r}\|^2$.

Note that in order to prevent overfitting, we can impose a regularized term to the above average reconstruction loss.

C. Denoising Autoencoder

The denoising autoencoders is a variant of the autoencoder that receives a corrupted input and is trained to reconstruct a clean 'repaired' input as its output [19]. By introducing a corruption process $C(\tilde{x}|x)$, the initial input x is transformed into a partially destroyed version $C(\tilde{x})$.

In this paper, we frame energy disaggregation of EV charging as a 'denoising' task. Typical denoising tasks include removing grain from an old photograph; or removing reverb from an audio recoding [25] and so on. For our problem, the corrupted input is the aggregated signal and the initial clean input is the ev signal. An denoising autoencoder attempts to remove the 'noise' produced by the other appliance from the aggregated signal. In other words, the ev signal is reconstructed from the aggregate power signal as the noisy input using a denoising autoencoder.

D. 1D Convolutional Neural Network

Convolutional Neural Networks are a specialized kind of neural network for processing data that has a known grid-like topology [29]. In our case, a small number of low level features are extracted by using one-dimensional (1D) convolutional network filters. The filters have a small receptive fileds across the entire input.

E. Proposed Architecture

According to the above subsection, the proposed architecture for energy disaggregation of EV charging can be designed as shown in Figure 4. The total number of parameters is 13834.

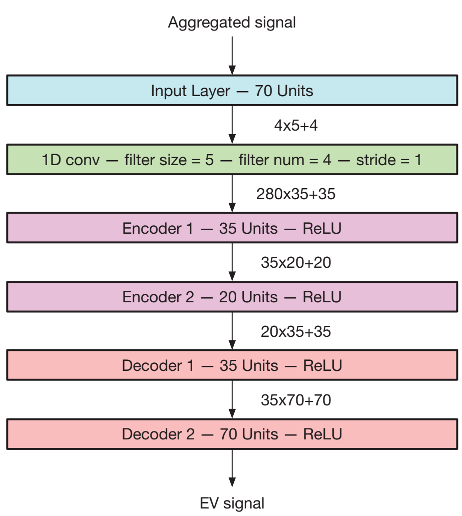

Fig. 4. Architecture of the proposed EV charging load disaggregation.

IV. Data Pre-processing

The denoising autoencoder is a type of neural network of which performance is very dependent its input, that is what you want it to memorize. So before training network, we need to pre-process the input data in order to improve its disaggregation performance.

A. Effective Interval

The effective interval is defined as an interval which belongs to a complete target appliance signal segment from the start time to the end time. Therefore, the length of an effective interval is determined by the corresponding working time of the target appliance. Figure 5 shows that one segment of aggregated power signals and its target appliance power signal segment are located in an effective interval. In an effective interval, it must have the "explicit" information (when only one appliance is working) that the target signal is the aggregated signal or the "implicit" information (when some appliances are working together) that the target signal contributes a share of waveform, and both of which give useful information to guide the task for energy disaggregation. Besides that, the introduction of the effective interval also gives a way of constructing the validation dataset which can provide an unbiased evaluation of a model fit on the training dataset while turning model hyperparameters.

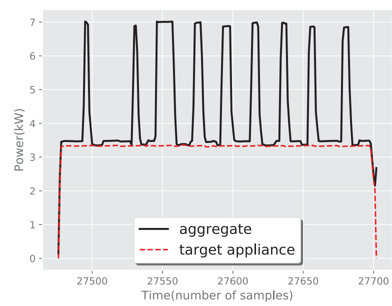

Fig. 5. One segment of aggregated power signals and its target appliance power signal segment are located in an effective interval.

B. Window Selection

The input size has an significant impact on the performance of our architecture. The input size depends on the slide window size. The over-short window can not capture the entire effective interval while the over-long window make neural network hard to learn useful information. Therefore, the window selection is very important. In this paper, we analyzed the limited number of labels and assume that the feasible selection range should be near the highest point of the density curve of on-duration as shown in Figure 6.

C. Filtering and Smoothing

There is a fact that if the amplitude of the aggregated signal below the minimum EV charging load signal, at that timestep the operation state of EV must be OFF. So we can filter a small number of signals whose amplitude is less than some threshold. In addition, we also filtered a part of spikes whose duration is less than some threshold based on the fact that if the length of the interval in the aggregated signal below the minimum on-duration of EV charging load signal, in that interval the operation state of EV must be OFF. After filtering, we used the quantization technique to properly smooth our aggregated signal [30].

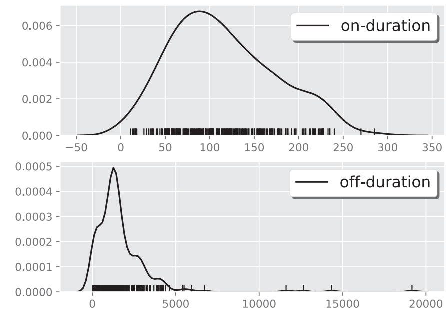

Fig. 6. The density curve of on-duration and off-duration for labels of training dataset.

D. Training Approaches

In this paper, we proposed a mini-batch training approach to reduce CPU running time. First, we constructed an effective training set denoted by $\boldsymbol{ET}$. Each sample must contain a part of effective interval. Second, we constructed a mixed training set denoted by $\boldsymbol{MT}$. Each sample is randomly selected from entire training dataset. Here, we define an ratio α to determine the size of a mixed training set as follows:

$$\alpha = \frac{|\boldsymbol{MT}|}{|\boldsymbol{ET}|} \tag{3}$$

where $|\boldsymbol{ET}|$ is the number of samples in an effective training set and $|\boldsymbol{MT}|$ is the number of samples in a mixed training set. If the sample in effective training set is the positive sample, to balance positive and negative sample α could be set at $1 \sim 1.5$. The final training set is the union of the above two sets. Moreover, it should be noted that a mixed training set is not unique and it will be updated in each iteration during training.

E. Standardization

Normally, neural networks learn most efficiently if the input data has zero mean. So we normalized our input data. Because we care about starting time and charging period, the scaling change after normalization does not matter. Labels are normalized using the Min-Max method.

V. Experimental Results

We used the data which came from the Pecan Street Database to validate the effectiveness of our methods for energy disaggregation of EV charging. The data collects raw power signals recorded from hundreds of residual houses in Austin, Texas. The sampling rate is 1/60 Hz. As experiment we randomly selected some houses. There are two metrics used to evaluate the performance of our methods:

$$reconstruction\ loss = \frac{1}{N}\sum_{i=0}^{N} \|\hat{\boldsymbol{y}}_{\boldsymbol{N}} - \boldsymbol{y}_{\boldsymbol{N}}\|_2^2 \tag{4}$$

$$MAE = \frac{1}{N}\sum_{i=0}^{N} |\hat{\boldsymbol{y}}_{\boldsymbol{N}} - \boldsymbol{y}_{\boldsymbol{N}}| : \hat{\boldsymbol{y}}_{\boldsymbol{N}}, \boldsymbol{y}_{\boldsymbol{N}} > 0 \leftarrow 1 \tag{5}$$

The reconstruction loss in equation (3) measures the mean square loss of the reconstruction compared to the ground truth, while the mean absolute error in equation (4) measures the accuracy of the predicted starting time and ending time in comparison to the ground truth.

We selected ”House ID 3367” one-year data as a training set and ”House ID 370/545/6139” one-year data as a testing set. We verified the generalization of one house to the other houses using two different training approaches. Table 1 shows the results and Figure 7 shows one example output produced by our method.

TABLE I. Performance of the Proposed method

ID(Tr)	ID(Te)	MAE(Entire)	MAE(Mini)	Reconstruction Loss
3367	370	0.115459	0.0671921	0.0502616
3367	545	0.129885	0.0620343	0.0476338
3367	6139	0.014553	0.0076316	0.0207514
—-	Avg	0.086632	0.0456193	0.0395489

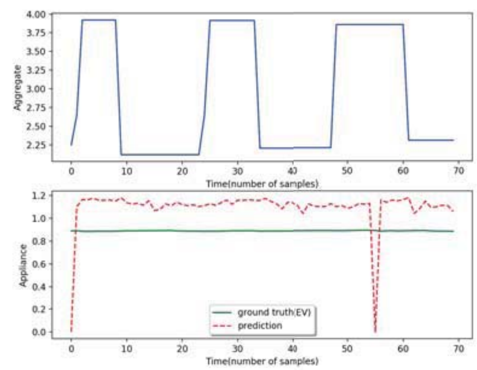

Fig. 7. One example output produced by the proposed method.

Table I shows that our method is effective and even if there is only one house, it can genralize to other unseen houses as well. Compared with two different training approaches, the mini-batch approach seems to perform better than the entire batch approach. It is shown in Fig.5 that the proposed method can disaggregate EV charging signal from the aggregated signal. Therefore, we can identify starting time and charging period.

VI. Conclusions and Future Work

This paper proposed an effective method to identify starting time and charging periods in EV charging profiles. We framed the EV charging profile identification problem as a denoising task and utilized a denoising autoencoder to disaggregate the EV charging from the aggregated power consumption signal from smart meters. The main contributions of this work lies in the fact that no similar techniques are existing to recognize and estimate EV charging profiles based on ubiquitously available data in a robust manner to support both distribution network operation and planning.

Several directions of future work are currently undergoing:

- the amount of training data we have used to test the idea of deep learning framework for EV charging profile identification was relatively small. The Pecan Street dataset has over 700 houses, each of which has an average of over 5 years of smart meter data. The performance of deep learning will greatly improve with massive amount of available data.
- the quality of available also needs to be evaluated. As Figure 7 shows, there are sudden dips of a very short time period in many data files, which can be reading errors of charging patterns. However, this observation of short dips has a negative impact on the performance of deep learning algorithms as it confuses the identifier.
- the performance of any algorithm based on the Pecan Street dataset needs to be evaluated, to determine how guaranteed the results can be extended to other EV charging profiles that are not labeled, i.e., ground truth is unknown.

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