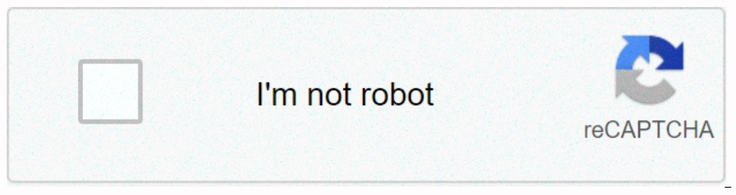

Continue

Which of the following is a representation learning algorithm

One solution to this problem is to use ML to detect not only the mapping from representation to production, but also the representation to itself. This approach is called representational learning. Mapping the representation to output is called the Hetero Association. Mapping the representation to itself is called Auto Association. Both approaches are about classification, but in the first case, associate a representation (or object, or item or vector) with a label (for a category other than the original represented object, item, or vector). In the second case, associate a representation (or object, or item or vector) with a label (for the original represented object, element, or vector). By impersonation they mean an image, object, element, vector, etc.. So an automatic associative coder can take a photo and output the category for the original image, while a straight associative tags can take a photo an output a learned association for that image (for example, the word dog). How would autoassociative learning be useful? Spell checking is a good example. Given a small lexicon of words (dog, hog, hat, warm) each word forms its own category, we can create an automatic codes that when presented with each word, featurizes the word, and returns the original category/word. Let's featurize the words using trigrams. So we share each word in the function set and allow this function set to represent the original word as follows: dog --> {' d', ' do', 'dog', 'and ', 'g '} --> dog pig --> {' h', 'ho', 'hog', 'and ', 'g '} --> hog hat --> {' h', 'ha', 'hat', 'on ', 't '} --> hat heat --> {' h', 'he', 'hea', 'eat', 'at ', 't '} -> heat Now we present a new word, featurize it, and see where it falls: hot --> {' h', 'ho', 'hot', 'ot', 't '} --> ??? hot matches 0% of the features of the dog. hot matches 40% of the features of hog. hot matches 40% of the features of the hat. hot matches 33% of the functions of heat. hot would be classified as either hog or hat if the match threshold was 40% or below. If we had a higher match threshold than 40% then there would be no match and thus no proper classification for the word hot. The automatic encoding of each of the encyclopedia entries (dog, hog, hat, heat) allowed us to take the original representation of each word and divide it into functions, which can be combined to point back to the original representation. dog --> {' d', 'do', 'dog', 'and ', 'g '} --> dog A heterocoding can take each of the encyclopedia entries and assign it to a different category. dog --> animal pig --> animal hat --> things heat --> thing a simple hash board can be enough as straight codes in this example. Neural networks take an input vector of functions and emit the category either an autoassociative or heterosexual manner. Part of a series of Machine Learning and Data Mining Problems Classification Clustering Clustering Anomaly Detection AutoML Association Rules Reinforcement Learning Structured Prediction Feature Engineering Feature Learning Online Learning Semi-supervised Learning Unattended Learning Learning Learning to Rank Grammar Induction Monitored Learning (Classification • Regression) Decision Trees Ensembles Bagging Boosting Random forest k-NN Linear Regression Naïve Bayes Artificial Neural Network Logistical Regression Grass Perceptron Relevance Vector Machine (RVM) Support Vector Machine (SVM) Clustering BIRCH CURE Hierarchical K-Means Anticipation Maximizing (EM) DBSCAN OPTICS Mean-Shift Dimensionality Reduction Factor Analysis CCA ICA LDA NMF PCA PGD T-SNE Textured Prediction Graphic Models Bayes net Conditional Random Field Hidden Markov Anomaly Detection k-NN Local External Factor Artificial Neural Network Autoencoder Deep Learning DeepDream Multilayer Perceptron RNN LSTM GRU ESN Limited Boltzmann Machine GAN AS Convolutional Neural Network U-Net Transformer Reinforcement Learning Q-Learning SARSA Temporal Difference (TD) Theory Bias Variance Dilemma Computational Learning Theory Empirical Risk Minimizing Occam Learning PAC Learning Statistical Learning VC Theory Machine Learning Arenas NeurIPS ICML ML JMLR ArXiv :cs. LG Artificial Intelligence Glossary Artificial Intelligence Glossary Related Articles List of Machine Learning Research Data Sets Overview Machine Learning Overview in Machine Learning is Functional Learning or Representation Learning[1] a set of techniques that allow a system to automatically detect the representations needed for function detection or classification from raw data. This replaces manual functional engineering and allows a machine to both learn the functions and use them to perform a specific task. Feature learning is motivated by the fact that machine learning tasks such as classification often require input that is mathematically and computationally convenient to process. However, data in the real world, such as images, video, and sensor data, has not given in to attempts to algorithm define specific functions. One option is to detect such features or representations through examination, without relying on explicit algorithms. Functional learning can either be monitored or unattended. In guided function learning, functions are learned using selected inputs. Examples include monitored neural networks, multilayered perceptron, and (monitored) dictionary learning. In unattended function learning, functions are learned with unmarked inputs. Examples include dictionary learning, independent component analysis, autocoders, matrix factorization[2] and various forms of clusters. [3] [4] [5] Supervised function learning is learning features from selected data. The data label allows the system to calculate an error period, the extent to which the system does not produce the label, which can then be used as to correct the learning process (reduce/minimize the error). Approaches include: Guided Dictionary Learning Dictionary Learning develops a set (dictionary) of representative elements from input, so that each data point can be represented as a weighted sum of the representative elements. The dictionary elements and weights can be found by minimizing the average impersonation error (over input), along with L1 regularization on the scales to enable thrift (that is, the representation of each data point has only a few non-zero weights). Guided dictionary learning leverages both the structure that under the influence of input and the labels for optimizing the dictionary items. For example, a guided dictionary learning technique[6] used dictionary learning on classification issues by optimizing the dictionary elements, weights to represent data points, and parameters for the classifier based on the input data. In particular, a minimization issue is formulated, where the lens function consists of the classification error, the representation error, an L1 regularization on those representing the weights of each data point (to enable sparse representation of data) and an L2 regularization on the parameters of the classifier. Neural networks Neural networks are a family of learning algorithms that use a network consisting of multiple layers of interconnected nodes. It is inspired by the animal nervous system, where the nodes are seen as neurons and edges are seen as synapses. Each edge has an associated weight, and the network defines calculation rules for transferring input from the network input layer to the output layer. A network function associated with a neural network characterizes the relationship between input and output layers, which are parameterized by the scales. With properly defined network features, various learning tasks can be performed by minimizing a cost function over the network function (weights). Multilayer neural networks can be used to perform functional learning, since they learn a representation of their input on the hidden layers that are later used for classification or regression on the output layer. The most popular network architecture of this type is Siamese networks. Unattended unattended feature learning is learning features from unmarked data. The goal of unattended function learning is often to detect low-dimensional features that capture a structure that under the foundation of the high-dimensional inputs. When function learning is performed in a way unattended, it enables a form of semi-monitored learning where features learned from an unmarked dataset are then used to improve performance in a monitored setting with selected data. [7] [8] Several approaches have been introduced in the following. K-means cluster k-mean clusters are a for vector quantification. Especially given a set of n vectors, k-means clustering groups them into k clusters (that is, subsets) in such a way that each vector belongs to the cluster with the nearest average. The problem is computationally NP-hard, although suboptimal greedy algorithms are developed. K-means clustering can be used to group an unmarked set of inputs into clusters, and then use the centroids of these clusters to produce functions. These features can be produced in several ways. The easiest is to add k binary functions to each sample, where each function j has value an iff jth centroid learned from k-means is closest to the sample under consideration. [3] It is also possible to use the distances of the clusters as functions, perhaps after transforming them through a radial base function (a technique that has been used to train RBF networks[9]). Coates and Ng note that certain variants of k-funds behave in the same way as sparse coding algorithms. [10] In a comparative evaluation of unattended learning methods, Coates, Lee, and Ng found that k-means clusters with an appropriate transformation surpass the newly invented automatic encoders and RBMs on an image classification task. [3] K-means also improves the performance of the nlp domain, especially for named device authentication; [11] There it competes with Brown clustering, as well as with distributed order presentations (also known as neural word embeds). [8] Master component analysis Master component analysis (PCA) is often used for dimension reduction. Given an unmarked set of n input data vectors, the PCA p (which is much smaller than the dimension of input) generates right one-digit vectors corresponding to the largest singular values of the data matrix, where the kth row of the data matrix is kth input data vector shifted by the example average of the input (that is, subtract sample average from data vector). Similarly, these singular vectors are eigenvectors that correspond to the largest eigenvalues of the sample covalance matrix of the input vectors. These on singular vectors are feature vectors learned from input, and they represent directions in which the data has the greatest variations. PCA is a linear function learning approach since on single vectors are linear functions of the data matrix. One vectors can be generated via a simple algorithm with p iterations. In the ith iteration, the projection of the data matrix is drawn on the (i-1)th eigenvector, and the ith singular vector exists as the right singular vector corresponding to the largest singular of the residual data matrix. PCA has several limitations. First, it assumes that the directions with great variance are of the most interest, which may not be the case. PCA relies only on orthogonal transformations of the original data, and it only the first- and second-order moments of the data, which may not well characterize the data distribution. Furthermore, the PCA can effectively reduce the dimension only when the input vectors are correlated (resulting in some dominant eigen values). Local Linear Embedding Local Linear Embedding (LLE) is a nonlinear learning approach to generate low-dimensional neighborly preservation representations from (unmarked) high-dimension input. The approach was proposed by Roweis and Saul (2000). [12] [13] The general idea of LLE is to reconstruct the original high-dimensional data using lower dimensional points while maintaining some geometric properties in the neighborhoods in the original dataset. LLE consists of two large steps. The first step is for neighboring preservation, where each input point Xi is reconstructed as a weighted sum by K's closest neighbor data points, and the optimal weights are found by minimizing the average squared reconstruction error (that is, the difference between an entry point and reconstruction) under the limitation that the weights associated with each point summarize to one. The second step is for dimension reduction, by looking for vectors in a lower dimensional space that minimizes the representation error using the optimized weights in the first step. Note that in the first step, the weights are optimized with fixed data, which can be solved as a minimum square problem. In the second step, lower-dimensional points are optimized with fixed weights, which can be solved via sparse eigenvalue degradation. The reconstruction scales obtained in the first step capture the inherent geometric properties of a neighborhood in input. [13] It is believed that original data is located on a smooth lower-dimensional manifold, and the inherent geometric properties captured by the weights of the original data are also expected to be on the manifold. This is why the same weights are used in the second step of LLE. Compared to PCA, LLE is more powerful when it comes to exploiting the underlying data structure. Independent component analysis Independent component analysis (ICA) is a technique for forming a data representation using a weighted sum of independent non-Gaussian components. [14] The assumption of non-Gaussian is imposed since the scales cannot be determined uniquely when all components follow Gaussian distribution. Unattended dictionary learning Unattended does not use dictionary learning to data labels and exploits the structure that under the data for optimizing dictionary elements. An example of unattended dictionary learning is sparse coding, which aims to learn basic functions (dictionary elements) for data representation from unmarked inputs. Sparse encoding can be used to learn overcomplete dictionaries, where the number of dictionary items is greater than the dimension of input. [15] Aharon et suggested algorithm K-SVD to learn a dictionary of elements that enable sparse representation. [16] Multilayer/deep architectures The hierarchical architecture of the biological neural system inspires deep learning architecture for functional learning by stacking multiple layers of learning nodes. [17] These architectures are often designed based on the assumption of distributed representation: observed data is generated by the interactions of many different factors on multiple levels. In a deep learning architecture, the output from each intermediate layer can be seen as a representation of the original input. Each level uses the representation produced by the previous level as input, producing new representations such as output, which are then fed to higher levels. The input on the bottom layer is raw data, and the output from the final layer is the final low-dimensional feature or representation. Limited Boltzmann machine Limited Boltzmann machines (RBMs) are often used as building blocks for multi-layer learning architectures. [3] [18] An RBM can be represented by an indirect bipartisan graph consisting of a group of binary hidden variables, a group of visible variables and edges that connect the hidden and visible nodes. It is a special case of the more general Boltzmann machines with the limitation of no intra-node connections. Each edge of an RBM is associated with a weight. The scales together with the compounds

define an energy function, based on which a common distribution of visible and hidden nodes can be prepared. Based on the topology of RBM, the hidden (visible) variables are independent, conditioned by the visible (hidden) variables. [clarification required] Such conditional independence facilitates calculations. An RBM can be seen as a single-layer architecture for unattended functional learning. In particular, the visible variables correspond to input, and the hidden variables correspond to function detectors. Weights can be trained by maximizing the likelihood of visible variables using Hinton's contrasting divergence algorithm (CD). [18] In general training, RBM by solving the maximizing problem tends to result in non-sparse representations. Sparse RBM was proposed to enable sparse representations. The idea is to add a regularization period to the target data probability function, which penalizes the deviation of the expected hidden variables from a small constant p {\displaystyle p} . Autoencoder An autocode consisting of a coder and a decoder is a paradigm for deep learning architectures. An example is provided by Hinton and Salakhutdinov[18] where the encoder uses raw data (e.g. image) as input and produces function or representation as output, and the decoder uses the extracted function from the encoder as input and reconstructs the original input raw data as output. The encoder and decoder are by stacking multiple layers of RBMs. The parameters involved in the architecture were originally trained in a greedy team-by-layer way: after one layer of function detectors are learned, they are tired of as visible variables for training similar to RBM. Current approaches typically apply end-to-end training with stochastic grading methods. Training can be repeated until some stop criteria are met. See also Automated Machine Learning (AutoML) Basic Function Deep Learning Function Detection (Computer Vision) Feature extraction Kernel trick Vector quantization References ^ Y. Bengio; A. Courville; In 2013, 100,000 people were released. In 2009, there were 100,000 employees in America, and in 2017 there were 100,000 employees IEEE transactions on pattern analysis and machine intelligence. 35 (8): 1798–1828. ArXiv:1206.5538. 10.1109/tpami.2013.50. In 1999, a ^ Nathan Srebro was published; Jason D.M. Rennie; Tommi S. Jaakkola (2004). Matrix factorization with maximum margin. Nips. ^ a b c d Coates, Adam; Lee, Honglak; Ng, Andrew Y. (2011). An analysis of single-layer networks in unattended function learning (PDF). Int'l Conf. on AI and Statistics (AISTATS). Archived from the original (PDF) on 13 February 2013. 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