Machine Learning Glossary

This glossary defines general machine learning terms as well as terms specific to TensorFlow.

A

A/B testing

A statistical way of comparing two (or more) techniques, typically an incumbent against a new rival. A/B testing aims to determine not only which technique performs better but also to understand whether the difference is statistically significant. A/B testing usually considers only two techniques using one measurement, but it can be applied to any finite number of techniques and measures.

accuracy

The fraction of predictions that a **classification model** (#classification_model) got right. In **multi-class classification** (#multi-class), accuracy is defined as follows:

$$\text{Accuracy} = \frac{\text{Correct Predictions}}{\text{Total Number Of Examples}}$$

In **binary classification** (#binary_classification), accuracy has the following definition:

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Number Of Examples}}$$

See **true positive** (#TP) and **true negative** (#TN).

activation function

A function (for example, **ReLU** (#ReLU) or **sigmoid** (#sigmoid_function)) that takes in the weighted sum of all of the inputs from the previous layer and then generates and passes an output value (typically nonlinear) to the next layer.

AdaGrad

A sophisticated gradient descent algorithm that rescales the gradients of each parameter, effectively giving each parameter an independent **learning rate** (#learning_rate). For a full explanation, see this paper (http://www.jmlr.org/papers/volume12/duchi11a/duchi11a.pdf).

AUC (Area under the ROC Curve)

An evaluation metric that considers all possible **classification thresholds** (#classification_threshold).

The Area Under the ROC curve (#ROC) is the probability that a classifier will be more confident that a randomly chosen positive example is actually positive than that a randomly chosen negative example is positive.

automation bias

When a human decision maker favors recommendations made by an automated decision-making system over information made without automation, even when the automated decision-making system makes errors.

B

backpropagation

The primary algorithm for performing **gradient descent** (#gradient_descent) on **neural networks** (#neural_network). First, the output values of each node are calculated (and cached) in a forward pass. Then, the partial derivative (https://wikipedia.org/wiki/Partial_derivative) of the error with respect to each parameter is calculated in a backward pass through the graph.

baseline

A simple **model** (#model) or heuristic used as reference point for comparing how well a model is performing. A baseline helps model developers quantify the minimal, expected performance on a particular problem.

batch

The set of examples used in one **iteration** (#iteration) (that is, one **gradient** (#gradient) update) of **model training** (#model_training).

See also **batch size** (#batch_size).

batch size

The number of examples in a **batch** (#batch). For example, the batch size of **SGD** (#SGD) is 1, while the batch size of a **mini-batch** (#mini-batch) is usually between 10 and 1000. Batch size is usually fixed during training and inference; however, TensorFlow does permit dynamic batch sizes.

bias (math)

An intercept or offset from an origin. Bias (also known as the **bias term**) is referred to as b or w_0 in machine learning models. For example, bias is the b in the following formula:

$$y' = b + w_1x_1 + w_2x_2 + \ldots w_nx_n$$

Not to be confused with **bias in ethics and fairness** (#bias_ethics) or **prediction bias** (#prediction_bias).

bias (ethics/fairness)

1. Stereotyping, prejudice or favoritism towards some things, people, or groups over others. These biases can affect collection and interpretation of data, the design of a system, and how users interact with a system. Forms of this type of bias include:

- **automation bias** (#automation_bias)
- **confirmation bias** (#confirmation_bias)
- **experimenter's bias** (#confirmation_bias)
- **group attribution bias** (#group_attribution_bias)
- **implicit bias** (#implicit_bias)
- **in-group bias** (#in-group_bias)
- **out-group homogeneity bias** (#out-group_homogeneity_bias)

2. Systematic error introduced by a sampling or reporting procedure. Forms of this type of bias include:

- **coverage bias** (#selection_bias)
- **non-response bias** (#selection_bias)
- **participation bias** (#participation_bias)
- **reporting bias** (#reporting_bias)
- **sampling bias** (#selection_bias)
- **selection bias** (#selection_bias)

Not to be confused with the bias term (#bias) in machine learning models or **prediction bias** (#prediction_bias)

binary classification

A type of classification task that outputs one of two mutually exclusive classes. For example, a machine learning model that evaluates email messages and outputs either "spam" or "not spam" is a binary classifier.

binning

See **bucketing** (#bucketing).

bucketing

Converting a (usually **continuous** (#continuous_feature)) feature into multiple binary features called buckets or bins, typically based on value range. For example, instead of representing temperature as a single continuous floating-point feature, you could chop ranges of temperatures into discrete bins. Given temperature data sensitive to a tenth of a degree, all temperatures between 0.0 and 15.0 degrees could be put into one bin, 15.1 to 30.0 degrees could be a second bin, and 30.1 to 50.0 degrees could be a third bin.

C

calibration layer

A post-prediction adjustment, typically to account for **prediction bias** (#prediction_bias). The adjusted predictions and probabilities should match the distribution of an observed set of labels.

candidate sampling

A training-time optimization in which a probability is calculated for all the positive labels, using, for example, softmax, but only for a random sample of negative labels. For example, if we have an example labeled *beagle* and *dog* candidate sampling computes the predicted probabilities and corresponding loss terms for the *beagle* and *dog* class outputs in addition to a random subset of the remaining classes (*cat*, *lollipop*, *fence*). The idea is that the **negative classes** (#negative_class) can learn from less frequent negative reinforcement as long as **positive classes** (#positive_class) always get proper positive reinforcement, and this is indeed observed empirically. The motivation for candidate sampling is a computational efficiency win from not computing predictions for all negatives.

categorical data

Features (#feature) having a discrete set of possible values. For example, consider a categorical feature named `house style`, which has a discrete set of three possible values: `Tudor, ranch, colonial`. By representing `house style` as categorical data, the model can learn the separate impacts of `Tudor`, `ranch`, and `colonial` on house price.

Sometimes, values in the discrete set are mutually exclusive, and only one value can be applied to a given example. For example, a `car maker` categorical feature would probably permit only a single value (`Toyota`) per example. Other times, more than one value may be applicable. A single car could be painted more than one different color, so a `car color` categorical feature would likely permit a single example to have multiple values (for example, `red` and `white`).

Categorical features are sometimes called **discrete features** (#discrete_feature).

Contrast with **numerical data** (#numerical_data).

centroid

The center of a cluster as determined by a **k-means** (#k-means) or **k-median** (#k-median) algorithm. For instance, if k is 3, then the k-means or k-median algorithm finds 3 centroids.

checkpoint

Data that captures the state of the variables of a model at a particular time. Checkpoints enable exporting model **weights** (#weight), as well as performing training across multiple sessions. Checkpoints also enable training to continue past errors (for example, job preemption). Note that the **graph** (#graph) itself is not included in a checkpoint.

class

One of a set of enumerated target values for a label. For example, in a **binary classification** (#binary_classification) model that detects spam, the two classes are *spam* and *not spam*. In a **multi-class classification** (#multi_class_classification) model that identifies dog breeds, the classes would be *poodle*, *beagle*, *pug*, and so on.

class-imbalanced data set

A **binary classification** (#binary_classification) problem in which the **labels** (#label) for the two classes have significantly different frequencies. For example, a disease data set in which 0.0001 of examples have positive labels and 0.9999 have negative labels is a class-imbalanced problem, but a football game predictor in which 0.51 of examples label one team winning and 0.49 label the other team winning is *not* a class-imbalanced problem.

classification model

A type of machine learning model for distinguishing among two or more discrete classes. For example, a natural language processing classification model could determine whether an input sentence was in French, Spanish, or Italian. Compare with **regression model** (#regression_model).

classification threshold

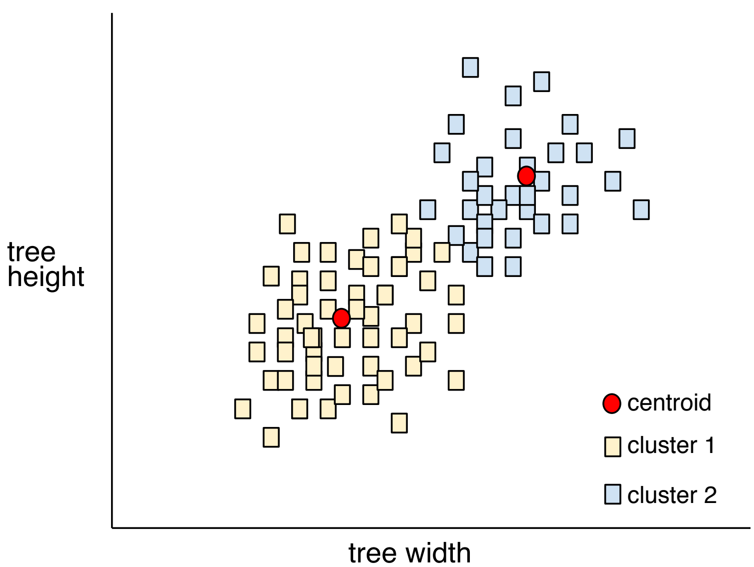
A scalar-value criterion that is applied to a model's predicted score in order to separate the **positive class** (#positive_class) from the **negative class** (#negative_class). Used when mapping

logistic regression (#logistic_regression) results to **binary classification** (#binary_classification). For example, consider a logistic regression model that determines the probability of a given email message being spam. If the classification threshold is 0.9, then logistic regression values above 0.9 are classified as *spam* and those below 0.9 are classified as *not spam*.

clustering

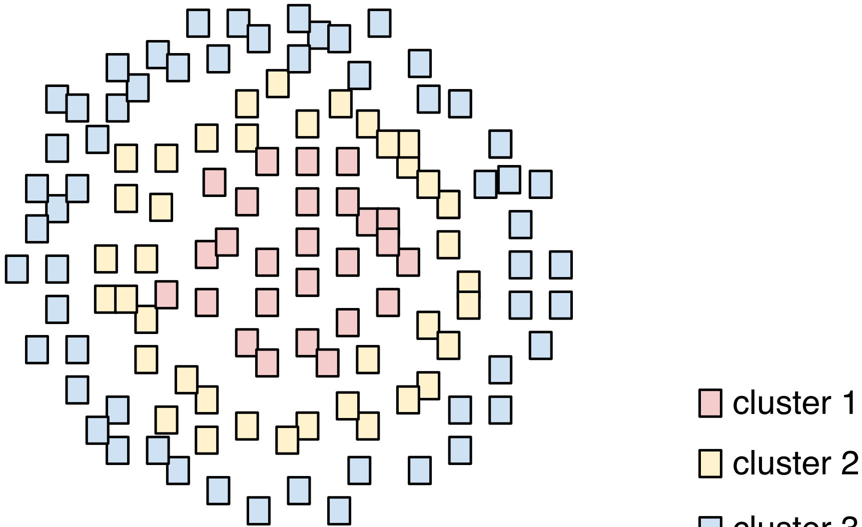
Grouping related **examples** (#example), particularly during **unsupervised learning** (#unsupervised_machine_learning). Once all the examples are grouped, a human can optionally supply meaning to each cluster.

Many clustering algorithms exist. For example, the **k-means** (#k-means) algorithm clusters examples based on their proximity to a **centroid** (#centroid), as in the following diagram:



A human researcher could then review the clusters and, for example, label cluster 1 as "dwarf trees" and cluster 2 as "full-size trees."

As another example, consider a clustering algorithm based on an example's distance from a center point, illustrated as follows:



collaborative filtering

Making predictions about the interests of one user based on the interests of many other users. Collaborative filtering is often used in recommendation systems.

confirmation bias

⚖️

The tendency to search for, interpret, favor, and recall information in a way that confirms one's preexisting beliefs or hypotheses. Machine learning developers may inadvertently collect or label data in ways that influence an outcome supporting their existing beliefs. Confirmation bias is a form of **implicit bias** (#implicit_bias).

Experimenter's bias is a form of confirmation bias in which an experimenter continues training models until a preexisting hypothesis is confirmed.

confusion matrix

An NxN table that summarizes how successful a **classification model's** (#classification_model) predictions were; that is, the correlation between the label and the model's classification. One axis of a confusion matrix is the label that the model predicted, and the other axis is the actual label. N represents the number of classes. In a **binary classification** (#binary_classification) problem, N=2. For example, here is a sample confusion matrix for a binary classification problem:

	Tumor (predicted)	Non-Tumor (predicted)
Tumor (actual)	18	1
Non-Tumor (actual)	6	452

The preceding confusion matrix shows that of the 19 samples that actually had tumors, the model correctly classified 18 as having tumors (18 true positives), and incorrectly classified 1 as not having a tumor (1 false negative). Similarly, of 458 samples that actually did not have tumors, 452 were correctly classified (452 true negatives) and 6 were incorrectly classified (6 false positives).

The confusion matrix for a multi-class classification problem can help you determine mistake patterns. For example, a confusion matrix could reveal that a model trained to recognize handwritten digits tends to mistakenly predict 9 instead of 4, or 1 instead of 7.

Confusion matrices contain sufficient information to calculate a variety of performance metrics, including **precision** (#precision) and **recall** (#recall).

continuous feature

A floating-point feature with an infinite range of possible values. Contrast with **discrete feature** (#discrete_feature).

convergence

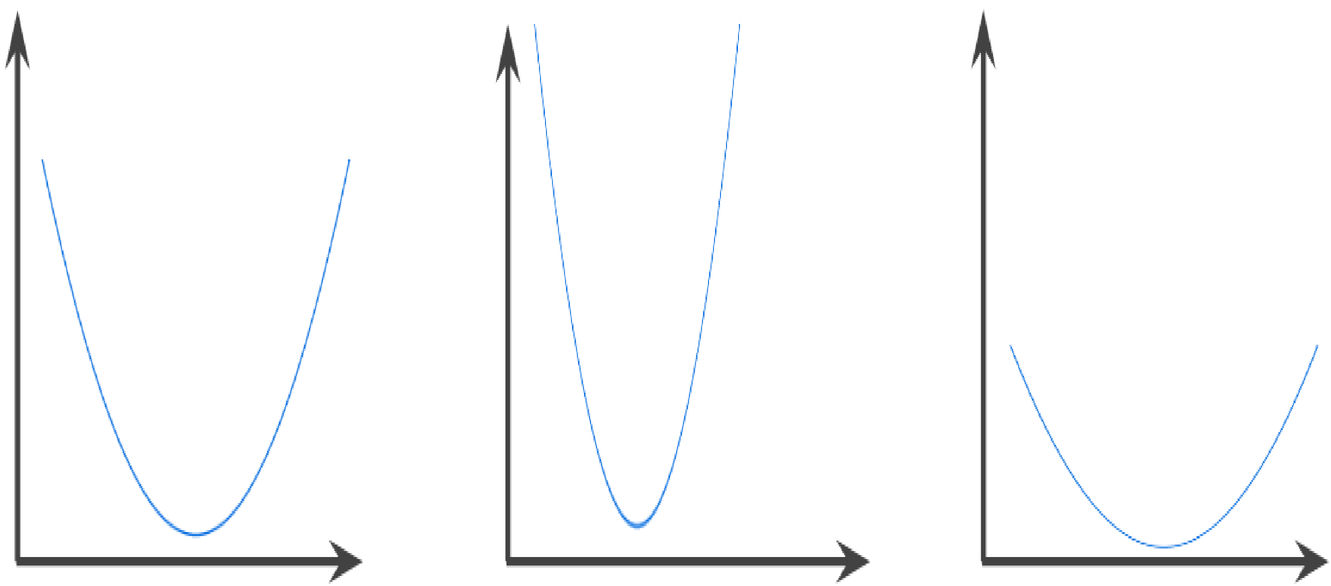
Informally, often refers to a state reached during training in which training **loss** (#loss) and validation loss change very little or not at all with each iteration after a certain number of iterations. In other words, a model reaches convergence when additional training on the current data will not improve the model. In deep learning, loss values sometimes stay constant or nearly so for many iterations before finally descending, temporarily producing a false sense of convergence.

See also **early stopping** (#early_stopping).

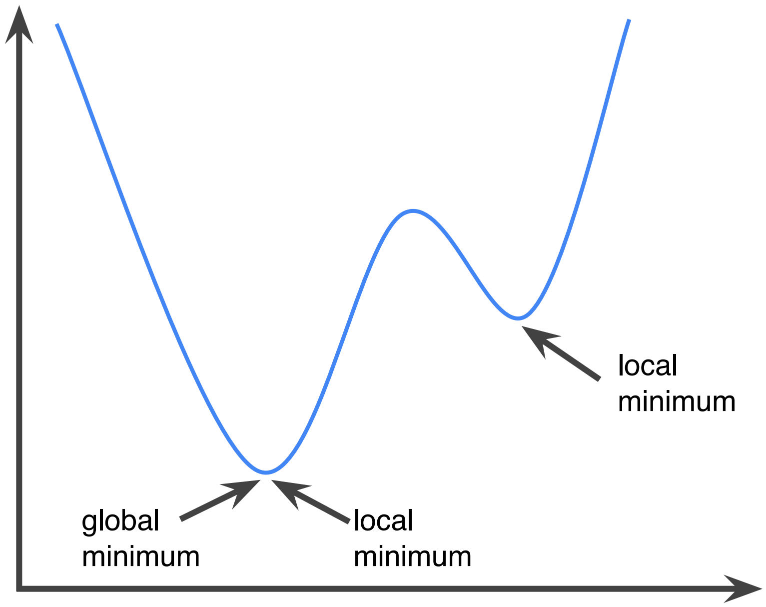
See also Boyd and Vandenberghe, Convex Optimization (https://web.stanford.edu/~boyd/cvxbook/bv_cvxbook.pdf).

convex function

A function in which the region above the graph of the function is a **convex set** (#convex_set). The prototypical convex function is shaped something like the letter **U**. For example, the following are all convex functions:



By contrast, the following function is not convex. Notice how the region above the graph is not a convex set:



A **strictly convex function** has exactly one local minimum point, which is also the global minimum point. The classic U-shaped functions are strictly convex functions. However, some convex functions (for example, straight lines) are not.

A lot of the common **loss functions** (#loss_functions), including the following, are convex functions:

- **L_2 loss** (#L2_loss)
- **Log Loss** (#Log_Loss)
- **L_1 regularization** (#L1_regularization)
- **L_2 regularization** (#L2_regularization)

Many variations of **gradient descent** (#gradient_descent) are guaranteed to find a point close to the minimum of a strictly convex function. Similarly, many variations of **stochastic gradient descent** (#SGD) have a high probability (though, not a guarantee) of finding a point close to the minimum of a strictly convex function.

The sum of two convex functions (for example, L_2 loss + L_1 regularization) is a convex function.

Deep models (#deep_model) are never convex functions. Remarkably, algorithms designed for **convex optimization** (#convex_optimization) tend to find reasonably good solutions on deep networks anyway, even though those solutions are not guaranteed to be a global minimum.

convex optimization

The process of using mathematical techniques such as **gradient descent** (#gradient_descent) to find the minimum of a **convex function** (#convex_function). A great deal of research in machine learning has focused on formulating various problems as convex optimization problems and in solving those problems more efficiently.

For complete details, see Boyd and Vandenberghe, Convex Optimization (https://web.stanford.edu/~boyd/cvxbook/bv_cvxbook.pdf).

convex set

A subset of Euclidean space such that a line drawn between any two points in the subset remains completely within the subset. For instance, the following two shapes are convex sets:

By contrast, the following two shapes are not convex sets:

convolution

In mathematics, casually speaking, a mixture of two functions. In machine learning, a convolution mixes the convolutional filter and the input matrix in order to train weights.

The term "convolution" in machine learning is often a shorthand way of referring to either **convolutional operation** (#convolutional_operation) or **convolutional layer** (#convolutional_layer).

Without convolutions, a machine learning algorithm would have to learn a separate weight for every cell in a large tensor. For example, a machine learning algorithm training on 2K x 2K images would be forced to find 4M separate weights. Thanks to convolutions, a machine learning algorithm only has to find weights for every cell in the **convolutional filter** (#convolutional_filter), dramatically reducing the memory needed to train the model. When the convolutional filter is applied, it is simply replicated across cells such that each is multiplied by the filter.

convolutional filter

One of the two actors in a **convolutional operation** (#convolutional_operation). (The other actor is a slice of an input matrix.) A convolutional filter is a matrix having the same **rank** (#rank) as the input matrix, but a smaller shape. For example, given a 28x28 input matrix, the filter could be any 2D matrix smaller than 28x28.

In photographic manipulation, all the cells in a convolutional filter are typically set to a constant pattern of ones and zeroes. In machine learning, convolutional filters are typically seeded with random numbers and then the network trains the ideal values.

convolutional layer

A layer of a deep neural network in which a **convolutional filter** (#convolutional_filter) passes along an input matrix. For example, consider the following 3x3 **convolutional filter** (#convolutional_filter):

0	1	0
1	0	1
0	1	0

The following animation shows a convolutional layer consisting of 9 convolutional operations involving the 5x5 input matrix. Notice that each convolutional operation works on a different 3x3 slice of the input matrix. The resulting 3x3 matrix (on the right) consists of the results of the 9 convolutional operations:

128	97	53	201	198
35	22	25	200	195
37	24	28	197	182
33	28	92	195	179
31	40	100	192	177

181		

convolutional neural network

A neural network in which at least one layer is a **convolutional layer** (#convolutional_layer). A typical convolutional neural network consists of some combination of the following layers:

- convolutional layers
- pooling layers
- dense layers

Convolutional neural networks have had great success in certain kinds of problems, such as image recognition.

convolutional operation

The following two-step mathematical operation:

1. Element-wise multiplication of the **convolutional filter** (#convolutional_filter) and a slice of an input matrix. (The slice of the input matrix has the same rank and size as the convolutional filter.)
2. Summation of all the values in the resulting product matrix.

For example, consider the following 5x5 input matrix:

128	97	53	201	198
35	22	25	200	195
37	24	28	197	182
33	28	92	195	179
31	40	100	192	177

Now imagine the following 2x2 convolutional filter:

1	0
0	1

Each convolutional operation involves a single 2x2 slice of the input matrix. For instance, suppose we use the 2x2 slice at the top-left of the input matrix. So, the convolution operation on this slice looks as follows:

$$\begin{bmatrix} 128 & 97 \\ 35 & 22 \end{bmatrix} \text{x} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \Rightarrow \begin{bmatrix} 128 & 0 \\ 0 & 22 \end{bmatrix} = \boxed{128+22=150}$$

A **convolutional layer** (#convolutional_layer) consists of a series of convolutional operations, each acting on a different slice of the input matrix.

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cost

Synonym for **loss** (#loss).

coverage bias

See **selection bias** (#selection_bias).

cross-entropy

A generalization of **Log Loss** (#Log_Loss) to **multi-class classification problems** (#multi-class). Cross-entropy quantifies the difference between two probability distributions. See also **perplexity** (#perplexity).

custom Estimator

An **Estimator** (#Estimators) that you write yourself by following these directions (https://www.tensorflow.org/get_started/custom_estimators).

Contrast with **premade Estimators** (#premade_Estimator).

D

data analysis

Obtaining an understanding of data by considering samples, measurement, and visualization. Data analysis can be particularly useful when a data set is first received, before one builds the first model. It is also crucial in understanding experiments and debugging problems with the system.

DataFrame

A popular datatype for representing data sets in Pandas. A DataFrame is analogous to a table. Each column of the DataFrame has a name (a header), and each row is identified by a number.

data set

A collection of **examples** (#example).

Dataset API (tf.data)

A high-level TensorFlow API for reading data and transforming it into a form that a machine learning algorithm requires. A `tf.data.Dataset` object represents a sequence of elements, in which each element contains one or more **Tensors** (#tensor). A `tf.data.Iterator` object provides access to the elements of a `Dataset`.

For details about the Dataset API, see Importing Data (https://www.tensorflow.org/programmers_guide/datasets) in the TensorFlow Programmer's Guide.

decision boundary

The separator between classes learned by a model in a **binary class** (#binary_classification) or **multi-class classification problems** (#multi-class). For example, in the following image representing a binary classification problem, the decision boundary is the frontier between the orange class and the blue class:

dense layer

Synonym for **fully connected layer** (#fully_connected_layer).

deep model

A type of **neural network** (#neural_network) containing multiple **hidden layers** (#hidden_layer). Deep models rely on trainable nonlinearities.

Contrast with **wide model** (#wide_model).

dense feature

A **feature** (#feature) in which most values are non-zero, typically a **Tensor** (#tensor) of floating-point values. Contrast with **sparse feature** (#sparse_features).

device

A category of hardware that can run a TensorFlow session, including CPUs, GPUs, and TPUs.

discrete feature

A **feature** (#feature) with a finite set of possible values. For example, a feature whose values may only be *animal*, *vegetable*, or *mineral* is a discrete (or categorical) feature. Contrast with **continuous feature** (#continuous_feature).

dropout regularization

A form of **regularization** (#regularization) useful in training **neural networks** (#neural_network). Dropout regularization works by removing a random selection of a fixed number of the units in a network layer for a single gradient step. The more units dropped out, the stronger the regularization. This is analogous to training the network to emulate an exponentially large ensemble of smaller networks. For full details, see Dropout: A Simple Way to Prevent Neural Networks from Overfitting (http://jmlr.org/papers/volume15/srivastava14a.old/srivastava14a.pdf).

dynamic model

A **model** (#model) that is trained online in a continuously updating fashion. That is, data is continuously entering the model.

E

early stopping

A method for **regularization** (#regularization) that involves ending model training *before* training loss finishes decreasing. In early stopping, you end model training when the loss on a **validation data set** (#validation_set) starts to increase, that is, when **generalization** (#generalization) performance worsens.

embeddings

A categorical feature represented as a continuous-valued feature. Typically, an embedding is a translation of a high-dimensional vector into a low-dimensional space. For example, you can represent the words in an English sentence in either of the following two ways:

- As a million-element (high-dimensional) **sparse vector** (#sparse_features) in which all elements are integers. Each cell in the vector represents a separate English word; the value in a cell represents the number of times that word appears in a sentence. Since a single English sentence is unlikely to contain more than 50 words, nearly every cell in the vector will contain a 0. The few cells that aren't 0 will contain a low integer (usually 1) representing the number of times that word appeared in the sentence.

- As a several-hundred-element (low-dimensional) **dense vector** (#dense_feature) in which each element holds a floating-point value between 0 and 1. This is an embedding.

In TensorFlow, embeddings are trained by **backpropagating** (#backpropagation) **loss** (#loss) just like any other parameter in a **neural network** (#neural_network).

empirical risk minimization (ERM)

Choosing the function that minimizes loss on the training set. Contrast with **structural risk minimization** (#SRM).

ensemble

A merger of the predictions of multiple **models** (#model). You can create an ensemble via one or more of the following:

- different initializations
- different **hyperparameters** (#hyperparameter)
- different overall structure

Deep and wide models (https://www.tensorflow.org/tutorials/wide_and_deep) are a kind of ensemble.

epoch

A full training pass over the entire data set such that each example has been seen once. Thus, an epoch represents `N`/**batch size** (#batch_size) training **iterations** (#iteration), where `N` is the total number of examples.

Estimator

An instance of the `tf.Estimator` class, which encapsulates logic that builds a TensorFlow graph and runs a TensorFlow session. You may create your own **custom Estimators** (#custom_estimator) (as described here (https://www.tensorflow.org/extend/estimators)) or instantiate **premade Estimators** (#premade_Estimator) created by others.

example

One row of a data set. An example contains one or more **features** (#feature) and possibly a **label** (#label). See also **labeled example** (#labeled_example) and **unlabeled example** (#unlabeled_example).

experimenter's bias

See **confirmation bias** (#confirmation_bias).

F

false negative (FN)

An example in which the model mistakenly predicted the **negative class** (#negative_class). For example, the model inferred that a particular email message was not spam (the negative class), but that email message actually was spam.

false positive (FP)

An example in which the model mistakenly predicted the **positive class** (#positive_class). For example, the model inferred that a particular email message was spam (the positive class), but that email message was actually not spam.

false positive rate (FP rate)

The x-axis in an **ROC curve** (#ROC). The FP rate is defined as follows:

$$\text{False Positive Rate} = \frac{\text{False Positives}}{\text{False Positives} + \text{True Negatives}}$$

feature

An input variable used in making **predictions** (#prediction).

Feature column (tf.feature_column)

A function that specifies how a model should interpret a particular feature. A list that collects the output returned by calls to such functions is a required parameter to all **Estimators** (#Estimators) constructors.

The `tf.feature_column` functions enable models to easily experiment with different representations of input features. For details, see the Feature Columns chapter (https://www.tensorflow.org/get_started/feature_columns) of the TensorFlow Programmers Guide.

"Feature column" is Google-specific terminology. A feature column is referred to as a "namespace" in the VW (https://wikipedia.org/wiki/Vowpal_Wabbit) system (at Yahoo/Microsoft), or a field (https://www.csie.ntu.edu.tw/~cjlin/libffm/).

feature cross

A **synthetic feature** (#synthetic_feature) formed by crossing (taking a **Cartesian product** (https://wikipedia.org/wiki/Cartesian_product) of) individual binary features obtained from **categorical data** (#categorical_data) or from **continuous features** (#continuous_feature) via **bucketing** (#bucketing). Feature crosses help represent nonlinear relationships.

feature engineering

The process of determining which **features** (#feature) might be useful in training a model, and then converting raw data from log files and other sources into said features. In TensorFlow, feature engineering often means converting raw log file entries to **tf.Example** (#tf.Example) protocol buffers. See also tf.Transform (https://github.com/tensorflow/transform).

Feature engineering is sometimes called **feature extraction**.

feature set

The group of **features** (#feature) your machine learning model trains on. For example, postal code, property size, and property condition might comprise a simple feature set for a model that predicts housing prices.

feature spec

Describes the information required to extract **features** (#feature) data from the **tf.Example** (#tf.Example) protocol buffer. Because the tf.Example protocol buffer is just a container for data, you must specify the following:

- the data to extract (that is, the keys for the features)
- the data type (for example, float or int)
- The length (fixed or variable)

The **Estimator API** (#Estimators) provides facilities for producing a feature spec from a list of **FeatureColumns** (#feature_columns).

few-shot learning

A machine learning approach, often used for object classification, designed to learn effective classifiers from only a small number of training examples.

See also **one-shot learning** (#one-shot_learning).

full softmax

See **softmax** (#softmax). Contrast with **candidate sampling** (#candidate_sampling).

fully connected layer

A **hidden layer** (#hidden_layer) in which each **node** (#node) is connected to *every* node in the subsequent hidden layer.

A fully connected layer is also known as a **dense layer** (#dense_layer).

G

generalization

Refers to your model's ability to make correct predictions on new, previously unseen data as opposed to the data used to train the model.

generalized linear model

A generalization of **least squares regression** (#least_squares_regression) models, which are based on Gaussian noise (https://wikipedia.org/wiki/Gaussian_noise), to other types of models based on other types of noise, such as Poisson noise (https://wikipedia.org/wiki/Shot_noise) or categorical noise. Examples of generalized linear models include:

- **logistic regression** (#logistic_regression)
- multi-class regression
- least squares regression

The parameters of a generalized linear model can be found through convex optimization (https://wikipedia.org/wiki/Convex_optimization).

Generalized linear models exhibit the following properties:

- The average prediction of the optimal least squares regression model is equal to the average label on the training data.
- The average probability predicted by the optimal logistic regression model is equal to the average label on the training data.

The power of a generalized linear model is limited by its features. Unlike a deep model, a generalized linear model cannot "learn new features."

gradient

The vector of **partial derivatives** (#partial_derivative) with respect to all of the independent variables. In machine learning, the gradient is the vector of partial derivatives of the model function. The gradient points in the direction of steepest ascent.

gradient clipping

Capping **gradient** (#gradient) values before applying them. Gradient clipping helps ensure numerical stability and prevents exploding gradients (http://www.cs.toronto.edu/~rgrosse/courses/csc321_2017/readings/L15 Exploding and Vanishing Gradients.pdf)
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gradient descent

A technique to minimize **loss** (#loss) by computing the gradients of loss with respect to the model's parameters, conditioned on training data. Informally, gradient descent iteratively adjusts parameters, gradually finding the best combination of **weights** (#weight) and bias to minimize loss.

graph

In TensorFlow, a computation specification. Nodes in the graph represent operations. Edges are directed and represent passing the result of an operation (a **Tensor** (#tensor)) as an operand to another operation. Use **TensorBoard** (#TensorBoard) to visualize a graph.

group attribution bias

Assuming that what is true for an individual is also true for everyone in that group. The effects of group attribution bias can be exacerbated if a convenience sample (https://wikipedia.org/wiki/Convenience_sampling) is used for data collection. In a non-representative sample, attributions may be made that do not reflect reality.

See also **out-group homogeneity bias** (#out-group_homogeneity_bias) and **in-group bias** (#in-group_bias).

H

heuristic

A practical and nonoptimal solution to a problem, which is sufficient for making progress or for learning from.

hidden layer

A synthetic layer in a **neural network** (#neural_network) between the **input layer** (#input_layer) (that is, the features) and the **output layer** (#output_layer) (the prediction). A neural network contains one or more hidden layers.

hinge loss

A family of **loss** (#loss) functions for **classification** (#classification_model) designed to find the **decision boundary** (#decision_boundary) as distant as possible from each training example, thus maximizing the margin between examples and the boundary. **KSVMs** (#KSVMs) use hinge loss (or a related function, such as squared hinge loss). For binary classification, the hinge loss function is defined as follows:

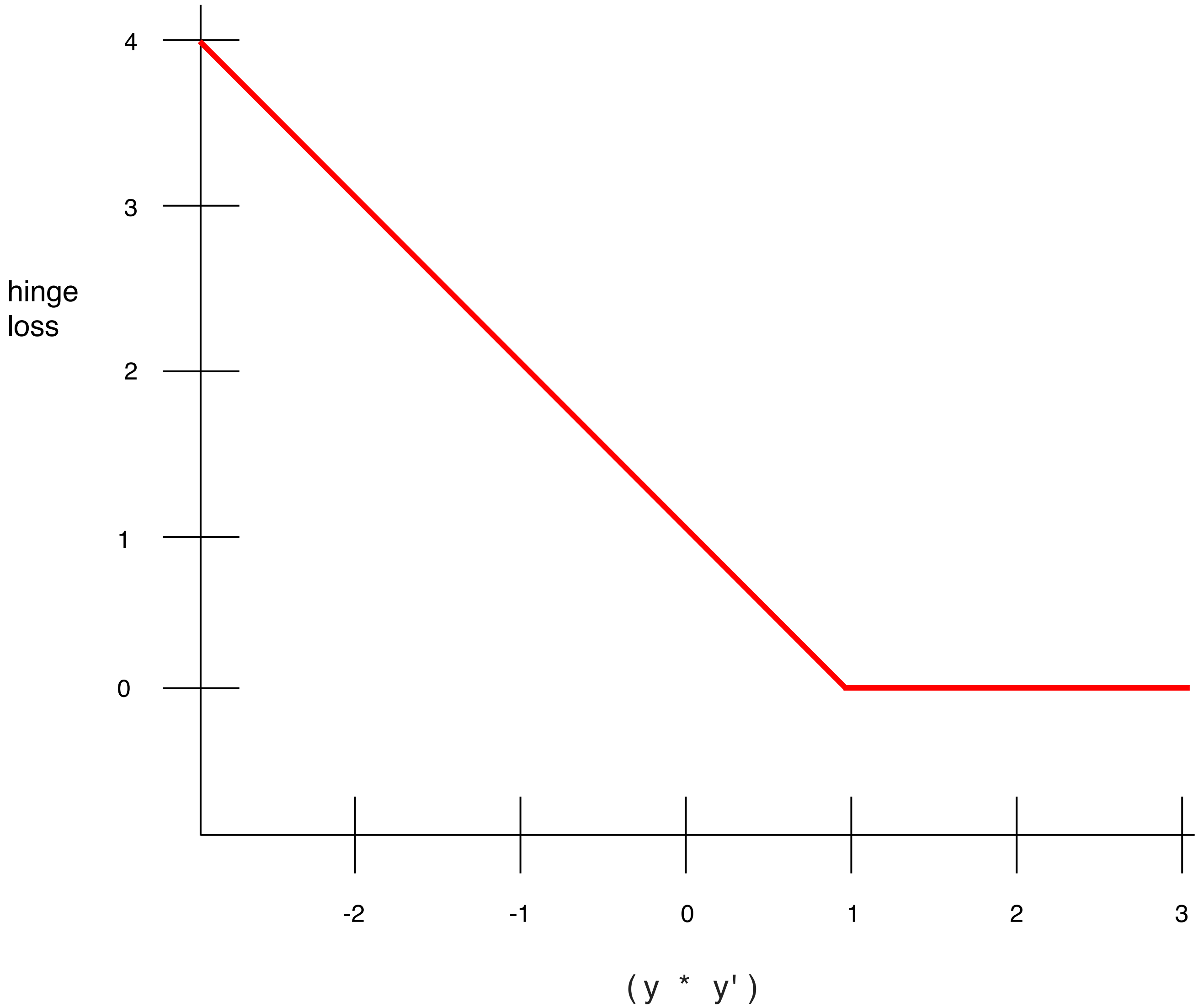
$$\text{loss} = \max(0, 1 - (y' * y))$$

where *y′* is the raw output of the classifier model:

$$y' = b + w_1x_1 + w_2x_2 + \ldots w_nx_n$$

and *y* is the true label, either -1 or +1.

Consequently, a plot of hinge loss vs. (y * y') looks as follows:



holdout data

Examples (#example) intentionally not used ("held out") during training. The **validation data set** (#validation_set) and **test data set** (#test_set) are examples of holdout data. Holdout data helps evaluate your model's ability to generalize to data other than the data it was trained on. The loss on the holdout set provides a better estimate of the loss on an unseen data set than does the loss on the training set.

hyperparameter

The "knobs" that you tweak during successive runs of training a model. For example, **learning rate** (#learning_rate) is a hyperparameter.

Contrast with **parameter** (#parameter).

hyperplane

A boundary that separates a space into two subspaces. For example, a line is a hyperplane in two dimensions and a plane is a hyperplane in three dimensions. More typically in machine learning, a hyperplane is the boundary separating a high-dimensional space. **Kernel Support Vector Machines** (#KSVMs) use hyperplanes to separate positive classes from negative classes, often in a very high-dimensional space.

I

implicit bias

Automatically making an association or assumption based on one's mental models and memories. Implicit bias can affect the following:

- How data is collected and classified.
- How ML systems are designed and developed.

For example, when building a classifier to identify wedding photos, an engineer may use the presence of a white dress in a photo as a feature. However, white dresses have been customary only during certain eras and in certain cultures.

See also **confirmation bias** (#confirmation_bias).

independently and identically distributed (i.i.d)

Data drawn from a distribution that doesn't change, and where each value drawn doesn't depend on values that have been drawn previously. An i.i.d. is the ideal gas (https://wikipedia.org/wiki/Ideal_gas) of machine learning—a useful mathematical construct but almost never exactly found in the real world. For example, the distribution of visitors to a web page may be i.i.d. over a brief window of time; that is, the distribution doesn't change during that brief window and one person's visit is generally independent of another's visit. However, if you expand that window of time, seasonal differences in the web page's visitors may appear.

inference

In machine learning, often refers to the process of making predictions by applying the trained model to **unlabeled examples** (#unlabeled_example). In statistics, inference refers to the process of fitting the parameters of a distribution conditioned on some observed data. (See the Wikipedia article on statistical inference (https://wikipedia.org/wiki/Statistical_inference).)

in-group bias

Showing partiality to one's own group or own characteristics. If testers or raters consist of the machine learning developer's friends, family, or colleagues, then in-group bias may invalidate product testing or the data set.

In-group bias is a form of **group attribution bias** (#group_attribution_bias). See also **out-group homogeneity bias** (#out-group_homogeneity_bias).

input function

In TensorFlow, a function that returns input data to the training, evaluation, or prediction method of an **Estimator** (#Estimators). For example, the training input function returns a **batch** (#batch) of features and labels from the **training set** (#training_set).

input layer

The first layer (the one that receives the input data) in a **neural network** (#neural_network).

instance

Synonym for **example** (#example).

interpretability

The degree to which a model's predictions can be readily explained. Deep models are often non-interpretable; that is, a deep model's different layers can be hard to decipher. By contrast, linear regression models and **wide models** (#wide_model) are typically far more interpretable.

inter-rater agreement

A measurement of how often human raters agree when doing a task. If raters disagree, the task instructions may need to be improved. Also sometimes called **inter-annotator agreement** or **inter-rater reliability**. See also Cohen's kappa (https://wikipedia.org/wiki/Cohen's_kappa), which is one of the most popular inter-rater agreement measurements.

iteration

A single update of a model's weights during training. An iteration consists of computing the gradients of the parameters with respect to the loss on a single **batch** (#batch) of data.

K

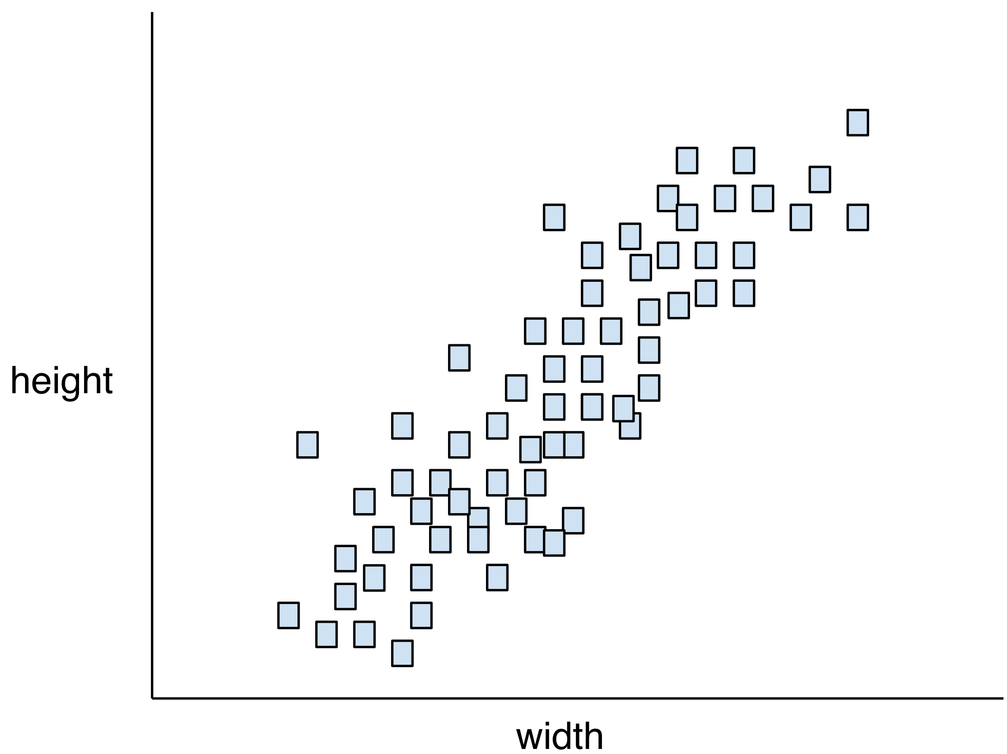
k-means

A popular **clustering** (#clustering) algorithm that groups examples in unsupervised learning. The k-means algorithm basically does the following:

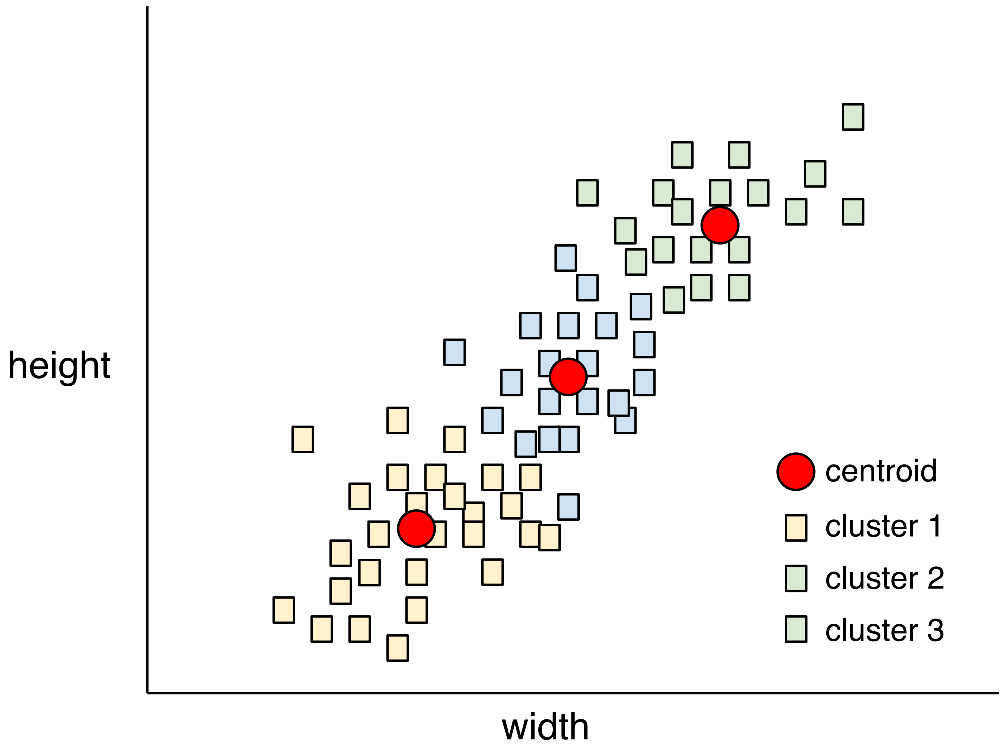
- Iteratively determines the best k center points (known as **centroids** (#centroid)).
- Assigns each example to the closest centroid. Those examples nearest the same centroid belong to the same group.

The k-means algorithm picks centroid locations to minimize the cumulative *square* of the distances from each example to its closest centroid.

For example, consider the following plot of dog height to dog width:



If k=3, the k-means algorithm will determine three centroids. Each example is assigned to its closest centroid, yielding three groups:



Imagine that a manufacturer wants to determine the ideal sizes for small, medium, and large sweaters for dogs. The three centroids identify the mean height and mean width of each dog in that cluster. So, the manufacturer should probably base sweater sizes on those three centroids. Note that the centroid of a cluster is typically *not* an example in the cluster.

The preceding illustrations shows k-means for examples with only two features (height and width). Note that k-means can group examples across many features.

k-median

A clustering algorithm closely related to **k-means** (#k-means). The practical difference between the two is as follows:

- In k-means, centroids are determined by minimizing the sum of the *squares* of the distance between a centroid candidate and each of its examples.
- In k-median, centroids are determined by minimizing the sum of the distance between a centroid candidate and each of its examples.

Note that the definitions of distance are also different:

- k-means relies on the Euclidean distance (https://wikipedia.org/wiki/Euclidean_distance) from the centroid to an example. (In two dimensions, the Euclidean distance means using the Pythagorean theorem to calculate the hypotenuse.) For example, the k-means distance between (2,2) and (5,-2) would be:

$$\text{Euclidean distance} = \sqrt{(2-5)^2 + (2--2)^2} = 5$$

- k-median relies on the Manhattan distance (https://wikipedia.org/wiki/Taxicab_geometry) from the centroid to an example. This distance is the sum of the absolute deltas in each dimension. For example, the k-median distance between (2,2) and (5,-2) would be:

$$\text{Manhattan distance} = |2-5| + |2--2| = 7$$

Keras

A popular Python machine learning API. Keras (https://keras.io) runs on several deep learning frameworks, including TensorFlow, where it is made available as **tf.keras** (https://www.tensorflow.org/api_docs/python/tf/keras).

Kernel Support Vector Machines (KSVMs)

A classification algorithm that seeks to maximize the margin between **positive** (#positive_class) and **negative classes** (#negative_class) by mapping input data vectors to a higher dimensional space. For example, consider a classification problem in which the input data set consists of a hundred features. In order to maximize the margin between positive and negative classes, KSVMs could internally map those features into a million-dimension space. KSVMs uses a loss function called hinge loss (#hinge-loss).

L

L_1 loss

Loss (#loss) function based on the absolute value of the difference between the values that a model is predicting and the actual values of the **labels** (#label). L_1 loss is less sensitive to outliers than **L_2 loss** (#squared_loss).

L_1 regularization

A type of **regularization** (#regularization) that penalizes weights in proportion to the sum of the absolute values of the weights. In models relying on **sparse features** (#sparse_features), L_1 regularization helps drive the weights of irrelevant or barely relevant features to exactly 0, which removes those features from the model. Contrast with **L_2 regularization** (#L2_regularization).

L_2 loss

See **squared loss** (#squared_loss).

L_2 regularization

A type of **regularization** (#regularization) that penalizes weights in proportion to the sum of the *squares* of the weights. L_2 regularization helps drive outlier weights (those with high positive or low negative values) closer to 0 but not quite to 0. (Contrast with **L1 regularization** (#L1_regularization).) L_2 regularization always improves generalization in linear models.

label

In supervised learning, the "answer" or "result" portion of an **example** (#example). Each example in a labeled data set consists of one or more features and a label. For instance, in a housing data set, the features might include the number of bedrooms, the number of bathrooms, and the age of the house, while the label might be the house's price. In a spam detection dataset, the features might include the subject line, the sender, and the email message itself, while the label would probably be either "spam" or "not spam."

labeled example

An example that contains **features** (#feature) and a **label** (#label). In supervised training, models learn from labeled examples.

lambda

Synonym for **regularization rate** (#regularization_rate).

(This is an overloaded term. Here we're focusing on the term's definition within **regularization** (#regularization).)

layer

A set of **neurons** (#neuron) in a **neural network** (#neural_network) that process a set of input features, or the output of those neurons.

Also, an abstraction in TensorFlow. Layers are Python functions that take **Tensors** (#tensor) and configuration options as input and produce other tensors as output. Once the necessary Tensors have been composed, the user can convert the result into an **Estimator** (#Estimators) via a **model function** (#model_function).

Layers API (tf.layers)

A TensorFlow API for constructing a **deep** (#deep_model) neural network as a composition of layers. The Layers API enables you to build different types of **layers** (#layer), such as:

- `tf.layers.Dense` for a **fully-connected layer** (#fully_connected_layer).
- `tf.layers.Conv2D` for a convolutional layer.

When writing a **custom Estimator** (#custom_estimator), you compose Layers objects to define the characteristics of all the **hidden layers** (#hidden_layers).

The Layers API follows the **Keras** (#Keras) layers API conventions. That is, aside from a different prefix, all functions in the Layers API have the same names and signatures as their counterparts in the Keras layers API.

learning rate

A scalar used to train a model via gradient descent. During each iteration, the **gradient descent** (#gradient_descent) algorithm multiplies the learning rate by the gradient. The resulting product is called the **gradient step**.

Learning rate is a key **hyperparameter** (#hyperparameter).

least squares regression

A linear regression model trained by minimizing **L_2 Loss** (#L2_loss).

linear regression

A type of **regression model** (#regression_model) that outputs a continuous value from a linear combination of input features.

logistic regression

A model that generates a probability for each possible discrete label value in classification problems by applying a **sigmoid function** (#sigmoid_function) to a linear prediction. Although logistic regression is often used in **binary classification** (#binary_classification) problems, it can also be used in **multi-class** (#multi-class) classification problems (where it becomes called **multi-class logistic regression** or **multinomial regression**).

logits

The vector of raw (non-normalized) predictions that a classification model generates, which is ordinarily then passed to a normalization function. If the model is solving a multi-class classification problem, logits typically become an input to the softmax function (https://www.tensorflow.org/api_docs/python/tf/nn/softmax_cross_entropy_with_logits_v2). The softmax function then generates a vector of (normalized) probabilities with one value for each possible class.

In addition, logits sometimes refer to the element-wise inverse of the **sigmoid function** (#sigmoid_function). For more information, see tf.nn.sigmoid_cross_entropy_with_logits (https://www.tensorflow.org/api_docs/python/tf/nn/sigmoid_cross_entropy_with_logits).

Log Loss

The **loss** (#loss) function used in binary **logistic regression** (#logistic_regression).

log-odds

The logarithm of the odds of some event.

If the event refers to a binary probability, then **odds** refers to the ratio of the probability of success (p) to the probability of failure (1-p). For example, suppose that a given event has a 90% probability of success and a 10% probability of failure. In this case, odds is calculated as follows:

$$\text{odds} = \frac{\text{p}}{\text{(1-p)}} = \frac{.9}{.1} = 9$$

The log-odds is simply the logarithm of the odds. By convention, "logarithm" refers to natural logarithm, but logarithm could actually be any base greater than 1. Sticking to convention, the log-odds of our example is therefore:

$$\text{log-odds} = ln(9) \; = 2.2$$

The log-odds are the inverse of the **sigmoid function** (#sigmoid_function).

loss

A measure of how far a model's **predictions** (#prediction) are from its **label** (#label). Or, to phrase it more pessimistically, a measure of how bad the model is. To determine this value, a model must define a loss function. For example, linear regression models typically use **mean squared error** (#MSE) for a loss function, while logistic regression models use **Log Loss** (#Log_Loss).

M

machine learning

A program or system that builds (trains) a predictive model from input data. The system uses the learned model to make useful predictions from new (never-before-seen) data drawn from the same distribution as the one used to train the model. Machine learning also refers to the field of study concerned with these programs or systems.

Mean Squared Error (MSE)

The average squared loss per example. MSE is calculated by dividing the **squared loss** (#squared_loss) by the number of **examples** (#example). The values that **TensorFlow Playground** (#TensorFlow_Playground) displays for "Training loss" and "Test loss" are MSE.

metric

A number that you care about. May or may not be directly optimized in a machine-learning system. A metric that your system tries to optimize is called an **objective** (#objective).

Metrics API (tf.metrics)

A TensorFlow API for evaluating models. For example, `tf.metrics.accuracy` determines how often a model's predictions match labels. When writing a **custom Estimator** (#custom_estimator), you invoke Metrics API functions to specify how your model should be evaluated.

mini-batch

A small, randomly selected subset of the entire batch of **examples** (#example) run together in a single iteration of training or inference. The **batch size** (#batch_size) of a mini-batch is usually between 10 and 1,000. It is much more efficient to calculate the loss on a mini-batch than on the full training data.

mini-batch stochastic gradient descent (SGD)

A **gradient descent** (#gradient_descent) algorithm that uses **mini-batches** (#mini-batch). In other words, mini-batch SGD estimates the gradient based on a small subset of the training data. **Vanilla SGD** (#SGD) uses a mini-batch of size 1.

ML

Abbreviation for **machine learning** (#machine_learning).

model

The representation of what an ML system has learned from the training data. Within TensorFlow, model is an overloaded term, which can have either of the following two related meanings:

- The **TensorFlow** (#TensorFlow) graph that expresses the structure of how a prediction will be computed.
- The particular weights and biases of that TensorFlow graph, which are determined by **training** (#model_training).

model function

The function within an **Estimator** (#Estimators) that implements ML training, evaluation, and inference. For example, the training portion of a model function might handle tasks such as defining the topology of a deep neural network and identifying its **optimizer** (#optimizer) function. When using **premade Estimators** (#premade_Estimator), someone has already written the model function for you. When using **custom Estimators** (#custom_estimator), you must write the model function yourself.

For details about writing a model function, see Creating Custom Estimators (https://www.tensorflow.org/get_started/custom_estimators).

model training

The process of determining the best **model** (#model).

Momentum

A sophisticated gradient descent algorithm in which a learning step depends not only on the derivative in the current step, but also on the derivatives of the step(s) that immediately preceded it. Momentum involves computing an exponentially weighted moving average of the gradients over time, analogous to momentum in physics. Momentum sometimes prevents learning from getting stuck in local minima.

multi-class classification

Classification problems that distinguish among more than two classes. For example, there are approximately 128 species of maple trees, so a model that categorized maple tree species would be multi-class. Conversely, a model that divided emails into only two categories (*spam* and *not spam*) would be a **binary classification model** (#binary_classification).

multinomial classification

Synonym for **multi-class classification** (#multi-class).

N

NaN trap

When one number in your model becomes a NaN (https://wikipedia.org/wiki/NaN) during training, which causes many or all other numbers in your model to eventually become a NaN.

NaN is an abbreviation for "Not a Number."

negative class

In **binary classification** (#binary_classification), one class is termed positive and the other is termed negative. The positive class is the thing we're looking for and the negative class is the other possibility. For example, the negative class in a medical test might be "not tumor." The negative class in an email classifier might be "not spam." See also **positive class** (#positive_class).

neural network

A model that, taking inspiration from the brain, is composed of layers (at least one of which is **hidden** (#hidden_layer)) consisting of simple connected units or **neurons** (#neuron) followed by nonlinearities.

neuron

A node in a **neural network** (#neural_network), typically taking in multiple input values and generating one output value. The neuron calculates the output value by applying an **activation function** (#activation_function) (nonlinear transformation) to a weighted sum of input values.

node (neural network)

A **neuron** (#neuron) in a **hidden layer** (#hidden_layer).

node (TensorFlow graph)

An operation in a TensorFlow **graph** (#graph).

non-response bias

See **selection bias** (#selection_bias).

normalization

The process of converting an actual range of values into a standard range of values, typically -1 to +1 or 0 to 1. For example, suppose the natural range of a certain feature is 800 to 6,000. Through subtraction and division, you can normalize those values into the range -1 to +1.

See also **scaling** (#scaling).

numerical data

Features (#feature) represented as integers or real-valued numbers. For example, in a real estate model, you would probably represent the size of a house (in square feet or square meters) as numerical data. Representing a feature as numerical data indicates that the feature's values have a *mathematical* relationship to each other and possibly to the label. For example, representing the size of a house as numerical data indicates that a 200 square-meter house is twice as large as a 100 square-meter house. Furthermore, the number of square meters in a house probably has some mathematical relationship to the price of the house.

Not all integer data should be represented as numerical data. For example, postal codes in some parts of the world are integers; however, integer postal codes should not be represented as numerical data in models. That's because a postal code of `20000` is not twice (or half) as potent as a postal code of 10000. Furthermore, although different postal codes *do* correlate to different real estate values, we can't assume that real estate values at postal code 20000 are twice as valuable as real estate values at postal code 10000. Postal codes should be represented as **categorical data** (#categorical_data) instead.

Numerical features are sometimes called **continuous features** (#continuous_feature).

numpy

An open-source math library (http://www.numpy.org/) that provides efficient array operations in Python. **pandas** (#pandas) is built on numpy.

O

objective

A metric that your algorithm is trying to optimize.

offline inference

Generating a group of **predictions** (#prediction), storing those predictions, and then retrieving those predictions on demand. Contrast with **online inference** (#online_inference).

one-hot encoding

A sparse vector in which:

- One element is set to 1.
- All other elements are set to 0.

One-hot encoding is commonly used to represent strings or identifiers that have a finite set of possible values. For example, suppose a given botany data set chronicles 15,000 different species, each denoted with a unique string identifier. As part of feature engineering, you'll probably encode those string identifiers as one-hot vectors in which the vector has a size of 15,000.

one-shot learning

A machine learning approach, often used for object classification, designed to learn effective classifiers from a single training example.

See also **few-shot learning** (#few-shot_learning).

one-vs.-all

Given a classification problem with N possible solutions, a one-vs.-all solution consists of N separate **binary classifiers** (#binary_classification)—one binary classifier for each possible outcome. For example, given a model that classifies examples as animal, vegetable, or mineral, a one-vs.-all solution would provide the following three separate binary classifiers:

- animal vs. not animal
- vegetable vs. not vegetable
- mineral vs. not mineral

online inference

Generating **predictions** (#prediction) on demand. Contrast with **offline inference** (#offline_inference).

Operation (op)

A node in the TensorFlow graph. In TensorFlow, any procedure that creates, manipulates, or destroys a **Tensor** (#tensor) is an operation. For example, a matrix multiply is an operation that takes two Tensors as input and generates one Tensor as output.

optimizer

A specific implementation of the **gradient descent** (#gradient_descent) algorithm. TensorFlow's base class for optimizers is tf.train.Optimizer (https://www.tensorflow.org/api_docs/python/tf/train/Optimizer). Different optimizers may leverage one or more of the following concepts to enhance the effectiveness of gradient descent on a given **training set** (#training_set):

- momentum (https://www.tensorflow.org/api_docs/python/tf/train/MomentumOptimizer) (Momentum)
- update frequency (AdaGrad (https://www.tensorflow.org/api_docs/python/tf/train/AdagradOptimizer) = ADAptive GRADient descent; Adam (https://www.tensorflow.org/api_docs/python/tf/train/AdamOptimizer) = ADAptive with Momentum; RMSProp)
- sparsity/regularization (Ftrl (https://www.tensorflow.org/api_docs/python/tf/train/FtrlOptimizer))
- more complex math (Proximal (https://www.tensorflow.org/api_docs/python/tf/train/ProximalGradientDescentOptimizer), and others)

You might even imagine an NN-driven optimizer (https://arxiv.org/abs/1606.04474).

out-group homogeneity bias

The tendency to see out-group members as more alike than in-group members when comparing attitudes, values, personality traits, and other characteristics. **In-group** refers to people you interact with regularly; **out-group** refers to people you do not interact with regularly. If you create a data set by asking people to provide attributes about out-groups, those attributes may be less nuanced and more stereotyped than attributes that participants list for people in their in-group.

For example, Lilliputians might describe the houses of other Lilliputians in great detail, citing small differences in architectural styles, windows, doors, and sizes. However, the same Lilliputians might simply declare that Brobdingnagians all live in identical houses.

Out-group homogeneity bias is a form of **group attribution bias** (#group_attribution_bias).

See also **in-group bias** (#in-group_bias).

outliers

Values distant from most other values. In machine learning, any of the following are outliers:

- **Weights** (#weight) with high absolute values.
- Predicted values relatively far away from the actual values.
- Input data whose values are more than roughly 3 standard deviations from the mean.

Outliers often cause problems in model training.

output layer

The "final" layer of a neural network. The layer containing the answer(s).

overfitting

Creating a model that matches the **training data** (#training_set) so closely that the model fails to make correct predictions on new data.

P

pandas

A column-oriented data analysis API. Many ML frameworks, including TensorFlow, support pandas data structures as input. See pandas documentation (http://pandas.pydata.org/).

parameter

A variable of a model that the ML system trains on its own. For example, **weights** (#weight) are parameters whose values the ML system gradually learns through successive training iterations. Contrast with **hyperparameter** (#hyperparameter).

Parameter Server (PS)

A job that keeps track of a model's **parameters** (#parameter) in a distributed setting.

See High-Performance Models (https://www.tensorflow.org/performance/performance_models) for details.

parameter update

The operation of adjusting a model's **parameters** (#parameter) during training, typically within a single iteration of **gradient descent** (#gradient_descent).

partial derivative

A derivative in which all but one of the variables is considered a constant. For example, the partial derivative of $f(x, y)$ with respect to x is the derivative of f considered as a function of x

alone (that is, keeping *y* constant). The partial derivative of *f* with respect to *x* focuses only on how *x* is changing and ignores all other variables in the equation.

participation bias

Synonym for non-response bias. See **selection bias** (#selection_bias).

partitioning strategy

The algorithm by which variables are divided across **parameter servers** (#Parameter_Server).

performance

Overloaded term with the following meanings:

- The traditional meaning within software engineering. Namely: How fast (or efficiently) does this piece of software run?
- The meaning within ML. Here, performance answers the following question: How correct is this **model** (#model)? That is, how good are the model's predictions?

perplexity

One measure of how well a **model** (#model) is accomplishing its task. For example, suppose your task is to read the first few letters of a word a user is typing on a smartphone keyboard, and to offer a list of possible completion words. Perplexity, P, for this task is approximately the number of guesses you need to offer in order for your list to contain the actual word the user is trying to type.

Perplexity is related to **cross-entropy** (#cross-entropy) as follows:

$$P = 2^{-\text{cross entropy}}$$

pipeline

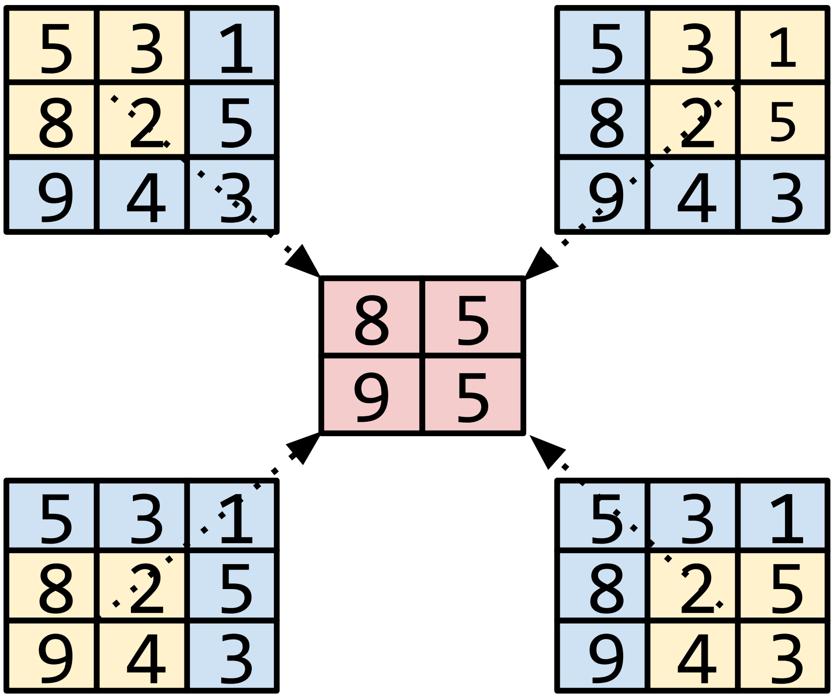
The infrastructure surrounding a machine learning algorithm. A pipeline includes gathering the data, putting the data into training data files, training one or more models, and exporting the models to production.

pooling

Reducing a matrix (or matrices) created by an earlier **convolutional layer** (#convolutional_layer) to a smaller matrix. Pooling usually involves taking either the maximum or average value across the pooled area. For example, suppose we have the following 3x3 matrix:

5	3	1
8	2	5
9	4	3

A pooling operation, just like a convolutional operation, divides that matrix into slices and then slides that convolutional operation by **strides** (#stride). For example, suppose the pooling operation divides the convolutional matrix into 2x2 slices with a 1x1 stride. As the following diagram illustrates, four pooling operations take place. Imagine that each pooling operation picks the maximum value of the four in that slice:



Pooling helps enforce **translational invariance** (#translational_invariance) in the input matrix.

Pooling for vision applications is known more formally as **spatial pooling**. Time-series applications usually refer to pooling as **temporal pooling**. Less formally, pooling is often called **subsampling** or **downsampling**.

positive class

In **binary classification** (#binary_classification), the two possible classes are labeled as positive and negative. The positive outcome is the thing we're testing for. (Admittedly, we're simultaneously testing for both outcomes, but play along.) For example, the positive class in a medical test might be "tumor." The positive class in an email classifier might be "spam."

Contrast with **negative class** (#negative_class).

precision

A metric for **classification models** (#classification_model). Precision identifies the frequency with which a model was correct when predicting the **positive class** (#positive_class). That is:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

prediction

A model's output when provided with an input **example** (#example).

prediction bias

A value indicating how far apart the average of **predictions** (#prediction) is from the average of **labels** (#label) in the data set.

Not to be confused with the bias term (#bias) in machine learning models or with **bias in ethics and fairness** (#bias_ethics).

premade Estimator

An **Estimator** (#Estimator) that someone has already built. TensorFlow provides several premade Estimators, including `DNNClassifier`, `DNNRegressor`, and `LinearClassifier`. To learn more about premade Estimators, see Premade Estimators (https://www.tensorflow.org/get_started/premade_estimators) or Premade Estimators for ML Beginners (https://www.tensorflow.org/get_started/get_started_for_beginners).

Contrast with **custom estimators** (#custom_estimator).

pre-trained model

Models or model components (such as **embeddings** (#embeddings)) that have been already been trained. Sometimes, you'll feed pre-trained embeddings into a **neural network**

(#neural_network). Other times, your model will train the embeddings itself rather than rely on the pre-trained embeddings.

prior belief

What you believe about the data before you begin training on it. For example, **L_2 regularization** (#L2_regularization) relies on a prior belief that **weights** (#weight) should be small and normally distributed around zero.

proxy labels

Data used to approximate labels not directly available in a data set.

For example, suppose you want *is it raining?* to be a Boolean label for your data set, but the data set doesn't contain rain data. If photographs are available, you might establish pictures of people carrying umbrellas as a proxy label for *is it raining?* However, proxy labels may distort results. For example, in some places, it may be more common to carry umbrellas to protect against sun than the rain.

Q

queue

A TensorFlow **Operation** (#Operation) that implements a queue data structure. Typically used in I/O.

R

rank (Tensor)

The number of dimensions in a **Tensor** (#tensor). For instance, a scalar has rank 0, a vector has rank 1, and a matrix has rank 2.

Not to be confused with **rank (ordinality)** (#rank_ordinality).

rank (ordinality)

The ordinal position of a class in an ML problem that categorizes classes from highest to lowest. For example, a behavior ranking system could rank a dog's rewards from highest (a steak) to lowest (wilted kale).

rater

A human who provides **labels** (#label) in **examples** (#example). Sometimes called an "annotator."

recall

A metric for **classification models** (#classification_model) that answers the following question: Out of all the possible positive labels, how many did the model correctly identify? That is:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

Rectified Linear Unit (ReLU)

An **activation function** (#activation_function) with the following rules:

- If input is negative or zero, output is 0.
- If input is positive, output is equal to input.

regression model

A type of model that outputs continuous (typically, floating-point) values. Compare with **classification models** (#classification_model), which output discrete values, such as "day lily" or "tiger lily."

regularization

The penalty on a model's complexity. Regularization helps prevent **overfitting** (#overfitting). Different kinds of regularization include:

- **L_1 regularization** (#L1_regularization)
- **L_2 regularization** (#L2_regularization)
- **dropout regularization** (#dropout_regularization)
- **early stopping** (#early_stopping) (this is not a formal regularization method, but can effectively limit overfitting)

regularization rate

A scalar value, represented as lambda, specifying the relative importance of the regularization function. The following simplified **loss** (#loss) equation shows the regularization rate's influence:

$$\text{minimize(loss function} + \lambda\text{(regularization function))}$$

Raising the regularization rate reduces **overfitting** (#overfitting) but may make the model less **accurate** (#accuracy).

reporting bias

The fact that the frequency with which people write about actions, outcomes, or properties is not a reflection of their real-world frequencies or the degree to which a property is characteristic of a class of individuals. Reporting bias can influence the composition of data that ML systems learn from.

For example, in books, the word *laughed* is more prevalent than *breathed*. An ML model that estimates the relative frequency of laughing and breathing from a book corpus would probably determine that laughing is more common than breathing.

representation

The process of mapping data to useful **features** (#feature).

ROC (receiver operating characteristic) Curve

A curve of **true positive rate** (#TP_rate) vs. **false positive rate** (#FP_rate) at different **classification thresholds** (#classification_threshold). See also **AUC** (#AUC).

root directory

The directory you specify for hosting subdirectories of the TensorFlow checkpoint and events files of multiple models.

Root Mean Squared Error (RMSE)

The square root of the **Mean Squared Error** (#MSE).

rotational invariance

In an image classification problem, an algorithm's ability to successfully classify images even when the orientation of the image changes. For example, the algorithm can still identify a tennis racket whether it is pointing up, sideways, or down. Note that rotational invariance is not always desirable; for example, an upside-down 9 should not be classified as a 9.

See also **translational invariance** (#translational_invariance) and **size invariance** (#size_invariance).

S

sampling bias

See **selection bias** (#selection_bias).

SavedModel

The recommended format for saving and recovering TensorFlow models. SavedModel is a language-neutral, recoverable serialization format, which enables higher-level systems and tools to produce, consume, and transform TensorFlow models.

See Saving and Restoring (https://www.tensorflow.org/programmers_guide/saved_model) in the TensorFlow Programmer's Guide for complete details.

Saver

A TensorFlow object (https://www.tensorflow.org/api_docs/python/tf/train/Saver) responsible for saving model checkpoints.

scaling

A commonly used practice in **feature engineering** (#feature_engineering) to tame a feature's range of values to match the range of other features in the data set. For example, suppose that you want all floating-point features in the data set to have a range of 0 to 1. Given a particular feature's range of 0 to 500, you could scale that feature by dividing each value by 500.

See also **normalization** (#normalization).

scikit-learn

A popular open-source ML platform. See www.scikit-learn.org (http://www.scikit-learn.org/).

selection bias

Errors in conclusions drawn from sampled data due to a selection process that generates systematic differences between samples observed in the data and those not observed. The following forms of selection bias exist:

- **coverage bias**: The population represented in the data set does not match the population that the ML model is making predictions about.
- **sampling bias**: Data is not collected randomly from the target group.
- **non-response bias** (also called **participation bias**): Users from certain groups opt-out of surveys at different rates than users from other groups.

For example, suppose you are creating an ML model that predicts people's enjoyment of a movie. To collect training data, you hand out a survey to everyone in the front row of a theater showing the movie. Offhand, this may sound like a reasonable way to gather a data set; however, this form of data collection may introduce the following forms of selection bias:

- coverage bias: By sampling from a population who chose to see the movie, your model's predictions may not generalize to people who did not already express that level of interest in the movie.
- sampling bias: Rather than randomly sampling from the intended population (all the people at the movie), you sampled only the people in the front row. It is possible that the people sitting in the front row were more interested in the movie than those in other rows.
- non-response bias: In general, people with strong opinions tend to respond to optional surveys more frequently than people with mild opinions. Since the movie survey is

optional, the responses are more likely to form a bimodal distribution (https://wikipedia.org/wiki/Multimodal_distribution) than a normal (bell-shaped) distribution.

semi-supervised learning

Training a model on data where some of the training examples have labels but others don't. One technique for semi-supervised learning is to infer labels for the unlabeled examples, and then to train on the inferred labels to create a new model. Semi-supervised learning can be useful if labels are expensive to obtain but unlabeled examples are plentiful.

sequence model

A model whose inputs have a sequential dependence. For example, predicting the next video watched from a sequence of previously watched videos.

session (tf.session)

An object that encapsulates the state of the TensorFlow run time and runs all or part of a **graph** (#graph). When using the low-level TensorFlow APIs, you instantiate and manage one or more `tf.session` objects directly. When using the Estimators API, Estimators instantiate session objects for you.

sigmoid function

A function that maps logistic or multinomial regression output (log odds) to probabilities, returning a value between 0 and 1. The sigmoid function has the following formula:

$$y = \frac{1}{1 + e^{-\sigma}}$$

where σ in **logistic regression** (#logistic_regression) problems is simply:

$$\sigma = b + w_1x_1 + w_2x_2 + \ldots w_nx_n$$

In other words, the sigmoid function converts σ into a probability between 0 and 1.

In some **neural networks** (#neural_network), the sigmoid function acts as the **activation function** (#activation_function).

size invariance

In an image classification problem, an algorithm's ability to successfully classify images even when the size of the image changes. For example, the algorithm can still identify a cat whether it consumes 2M pixels or 200K pixels. Note that even the best image classification algorithms still have practical limits on size invariance. For example, an algorithm (or human) is unlikely to correctly classify a cat image consuming only 20 pixels.

See also **translational invariance** (#translational_invariance) and **rotational invariance** (#rotational_invariance).

softmax

A function that provides probabilities for each possible class in a **multi-class classification model** (#multi-class). The probabilities add up to exactly 1.0. For example, softmax might determine that the probability of a particular image being a dog at 0.9, a cat at 0.08, and a horse at 0.02. (Also called **full softmax**.)

Contrast with **candidate sampling** (#candidate_sampling).

sparse feature

Feature (#feature) vector whose values are predominately zero or empty. For example, a vector containing a single 1 value and a million 0 values is sparse. As another example, words in a search query could also be a sparse feature—there are many possible words in a given language, but only a few of them occur in a given query.

Contrast with **dense feature** (#dense_feature).

sparse representation

A **representation** (#representation) of a tensor that only stores nonzero elements.

For example, the English language consists of about a million words. Consider two ways to represent a count of the words used in one English sentence:

- A **dense representation** of this sentence must set an integer for all one million cells, placing a 0 in most of them, and a low integer into a few of them.
- A sparse representation of this sentence stores only those cells symbolizing a word actually in the sentence. So, if the sentence contained only 20 unique words, then the sparse representation for the sentence would store an integer in only 20 cells.

For example, consider two ways to represent the sentence, "Dogs wag tails." As the following tables show, the dense representation consumes about a million cells; the sparse representation consumes only 3 cells:

Dense Representation

Cell Number	Word	Occurrence
0	a	0
1	aardvark	0
2	aargh	0
3	aarti	0
… 140,391 more words with an occurrence of 0		
140395	dogs	1
… 633,062 words with an occurrence of 0		
773458	tails	1
… 189,136 words with an occurrence of 0		

Cell Number	Word	Occurrence
962594	wag	1

… many more words with an occurrence of 0

Sparse Representation

Cell Number	Word	Occurrence
140395	dogs	1
773458	tails	1
962594	wag	1

sparsity

The number of elements set to zero (or null) in a vector or matrix divided by the total number of entries in that vector or matrix. For example, consider a 10x10 matrix in which 98 cells contain zero. The calculation of sparsity is as follows:

$$\text{sparsity} = \frac{98}{100} = 0.98$$

Feature sparsity refers to the sparsity of a feature vector; **model sparsity** refers to the sparsity of the model weights.

spatial pooling

See **pooling** (#pooling).

squared hinge loss

The square of the **hinge loss** (#hinge-loss). Squared hinge loss penalizes outliers more harshly than regular hinge loss.

squared loss

The **loss** (#loss) function used in **linear regression** (#linear_regression). (Also known as **L_2 Loss**.) This function calculates the squares of the difference between a model's predicted value for a labeled **example** (#example) and the actual value of the **label** (#label). Due to squaring, this loss function amplifies the influence of bad predictions. That is, squared loss reacts more strongly to outliers than **L_1 loss** (#L1_loss).

static model

A model that is trained offline.

stationarity

A property of data in a data set, in which the data distribution stays constant across one or more dimensions. Most commonly, that dimension is time, meaning that data exhibiting stationarity doesn't change over time. For example, data that exhibits stationarity doesn't change from September to December.

step

A forward and backward evaluation of one **batch** (#batch).

step size

Synonym for **learning rate** (#learning_rate).

stochastic gradient descent (SGD)

A **gradient descent** (#gradient_descent) algorithm in which the batch size is one. In other words, SGD relies on a single example chosen uniformly at random from a data set to calculate an estimate of the gradient at each step.

stride

In a convolutional operation or pooling, the delta in each dimension of the next series of input slices. For example, the following animation demonstrates a (1,1) stride during a convolutional operation. Therefore, the next input slice starts one position to the right of the previous input slice. When the operation reaches the right edge, the next slice is all the way over to the left but one position down.

128	97	53	201	198
35	22	25	200	195
37	24	28	197	182
33	28	92	195	179
31	40	100	192	177

181		

The preceding example demonstrates a two-dimensional stride. If the input matrix is three-dimensional, the stride would also be three-dimensional.

structural risk minimization (SRM)

An algorithm that balances two goals:

- The desire to build the most predictive model (for example, lowest loss).
- The desire to keep the model as simple as possible (for example, strong regularization).

For example, a function that minimizes loss+regularization on the training set is a structural risk minimization algorithm.

For more information, see http://www.svms.org/srm/ (http://www.svms.org/srm/).

Contrast with **empirical risk minimization** (#ERM).

subsampling

See **pooling** (#pooling).

summary

In TensorFlow, a value or set of values calculated at a particular **step** (#step), usually used for tracking model metrics during training.

supervised machine learning

Training a **model** (#model) from input data and its corresponding **labels** (#label). Supervised machine learning is analogous to a student learning a subject by studying a set of questions and their corresponding answers. After mastering the mapping between questions and answers, the student can then provide answers to new (never-before-seen) questions on the same topic. Compare with **unsupervised machine learning** (#unsupervised_machine_learning).

synthetic feature

A **feature** (#feature) not present among the input features, but created from one or more of them. Kinds of synthetic features include:

- **Bucketing** (#bucketing) a continuous feature into range bins.
- Multiplying (or dividing) one feature value by other feature value(s) or by itself.
- Creating a **feature cross** (#feature_cross).

Features created by **normalizing** (#normalization) or **scaling** (#scaling) alone are not considered synthetic features.

T

target

Synonym for **label** (#label).

temporal data

Data recorded at different points in time. For example, winter coat sales recorded for each day of the year would be temporal data.

Tensor

The primary data structure in TensorFlow programs. Tensors are N-dimensional (where N could be very large) data structures, most commonly scalars, vectors, or matrices. The elements of a Tensor can hold integer, floating-point, or string values.

Tensor Processing Unit (TPU)

An ASIC (application-specific integrated circuit) that optimizes the performance of TensorFlow programs.

Tensor rank

See **rank (Tensor)** (#rank_Tensor).

Tensor shape

The number of elements a **Tensor** (#tensor) contains in various dimensions. For example, a [5, 10] Tensor has a shape of 5 in one dimension and 10 in another.

Tensor size

The total number of scalars a **Tensor** (#tensor) contains. For example, a [5, 10] Tensor has a size of 50.

TensorBoard

The dashboard that displays the summaries saved during the execution of one or more TensorFlow programs.

TensorFlow

A large-scale, distributed, machine learning platform. The term also refers to the base API layer in the TensorFlow stack, which supports general computation on dataflow graphs.

Although TensorFlow is primarily used for machine learning, you may also use TensorFlow for non-ML tasks that require numerical computation using dataflow graphs.

TensorFlow Playground

A program that visualizes how different **hyperparameters** (#hyperparameter) influence model (primarily neural network) training. Go to http://playground.tensorflow.org (http://playground.tensorflow.org) to experiment with TensorFlow Playground.

TensorFlow Serving

A platform to deploy trained models in production.

test set

The subset of the data set that you use to test your **model** (#model) after the model has gone through initial vetting by the validation set.

Contrast with **training set** (#training_set) and **validation set** (#validation_set).

tf.Example

A standard protocol buffer (https://developers.google.com/protocol-buffers/) for describing input data for machine learning model training or inference.

time series analysis

A subfield of machine learning and statistics that analyzes **temporal data** (#temporal_data). Many types of machine learning problems require time series analysis, including classification, clustering, forecasting, and anomaly detection. For example, you could use time series analysis to forecast the future sales of winter coats by month based on historical sales data.

training

The process of determining the ideal **parameters** (#parameter) comprising a model.

training set

The subset of the data set used to train a model.

Contrast with **validation set** (#validation_set) and **test set** (#test_set).

transfer learning

Transferring information from one machine learning task to another. For example, in multi-task learning, a single model solves multiple tasks, such as a **deep model** (#deep_model) that has different output nodes for different tasks. Transfer learning might involve transferring knowledge from the solution of a simpler task to a more complex one, or involve transferring knowledge from a task where there is more data to one where there is less data.

Most machine learning systems solve a *single* task. Transfer learning is a baby step towards artificial intelligence in which a single program can solve *multiple* tasks.

translational invariance

In an image classification problem, an algorithm's ability to successfully classify images even when the position of objects within the image changes. For example, the algorithm can still identify a dog, whether it is in the center of the frame or at the left end of the frame.

See also **size invariance** (#size_invariance) and **rotational invariance** (#rotational_invariance).

true negative (TN)

An example in which the model *correctly* predicted the **negative class** (#negative_class). For example, the model inferred that a particular email message was not spam, and that email message really was not spam.

true positive (TP)

An example in which the model *correctly* predicted the **positive class** (#positive_class). For example, the model inferred that a particular email message was spam, and that email message really was spam.

true positive rate (TP rate)

Synonym for **recall** (#recall). That is:

$$\text{True Positive Rate} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

True positive rate is the y-axis in an **ROC curve** (#ROC).

U

unlabeled example

An example that contains **features** (#feature) but no **label** (#label). Unlabeled examples are the input to **inference** (#inference). In **semi-supervised** (#semi-supervised_learning) and **unsupervised** (#unsupervised_machine_learning) learning, unlabeled examples are used during training.

unsupervised machine learning

Training a **model** (#model) to find patterns in a data set, typically an unlabeled data set.

The most common use of unsupervised machine learning is to cluster data into groups of similar examples. For example, an unsupervised machine learning algorithm can cluster songs together based on various properties of the music. The resulting clusters can become an input to other machine learning algorithms (for example, to a music recommendation service). Clustering can be helpful in domains where true labels are hard to obtain. For example, in domains such as anti-abuse and fraud, clusters can help humans better understand the data.

Another example of unsupervised machine learning is **principal component analysis (PCA)** (https://wikipedia.org/wiki/Principal_component_analysis). For example, applying PCA on a data set containing the contents of millions of shopping carts might reveal that shopping carts containing lemons frequently also contain antacids.

Compare with **supervised machine learning** (#supervised_machine_learning).

V

validation set

A subset of the data set—disjunct from the training set—that you use to adjust **hyperparameters** (#hyperparameter).

Contrast with **training set** (#training_set) and **test set** (#test_set).

W

weight

A coefficient for a **feature** (#feature) in a linear model, or an edge in a deep network. The goal of training a linear model is to determine the ideal weight for each feature. If a weight is 0, then its corresponding feature does not contribute to the model.

wide model

A linear model that typically has many **sparse input features** (#sparse_features). We refer to it as "wide" since such a model is a special type of **neural network** (#neural_network) with a large number of inputs that connect directly to the output node. Wide models are often easier to debug and inspect than deep models. Although wide models cannot express nonlinearities through **hidden layers** (#hidden_layer), they can use transformations such as **feature crossing** (#feature_cross) and **bucketization** (#bucketing) to model nonlinearities in different ways.

Contrast with **deep model** (#deep_model).

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