Notation

Machine Learning - Section 1.1.1

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In machine learning, data comes in the form of the **outcome** we wish to predict, and the **features** to be used to predict the outcome. Our goal: Build an algorithm that takes features as inputs, and returns a prediction for the unknown outcome. Specifically, Machine Learning involves the use of a dataset of known outcomes to train our algorithm to predict the outcomes of similar datasets with unknown outcomes. Y is used to denote outcomes; and $X_1, ... X_p$ is used to denote the various features. Features are also referred to as **predictors** and **covariates**.

Prediction problems are divided into Categorical outcomes and Continuous outcomes.

For Categorical outcomes, Y can be any of K classes: $Y_1, ..., Y_K$. For example, an algorithm that is trained to read digits has K = 10, with the classes being [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]. In speech recognition, the outcome is all of the possible words we are trying to detect. Spam detection has two outcomes, spam or not spam. Thus, for binary data we use k = 0, 1, since there are only 2 outcomes.

General Setup: We have a series of features and an unknown outcome we wish to predict.

| outcome | feature_1 | feature_2 | feature_3 | feature_4 | feature_5 |
|---------|-----------|-----------|-----------|-----------|-----------|
| ? | X_1 | X_2 | X_3 | X_4 | X_5 |

To build an algorithm that can predict the above unknown outcome we collect data for which we do know the outcome.

| outcome | $feature_1$ | $feature_2$ | $feature_3$ | $feature_4$ | feature_5 |
|---------|--------------|--------------|--------------|--------------|-----------|
| Y_1 | X_1,1 | X_2,1 | X_3,1 | X_4,1 | X_5,1 |
| Y_2 | $X_{1,2}$ | $X_{2,2}$ | $X_{3,2}$ | $X_{4,2}$ | $X_{5,2}$ |
| Y_3 | $X_{1,3}$ | $X_{2,3}$ | $X_{3,3}$ | $X_{4,3}$ | $X_{5,3}$ |
| Y_4 | $X_{1,4}$ | $X_{2,4}$ | $X_{3,4}$ | $X_{4,4}$ | $X_{5,4}$ |
| Y_5 | X_1,5 | $X_{2,5}$ | X_3,5 | $X_{4,5}$ | X_5,5 |

We use \hat{Y} to denote **prediction**. The term "actual outcome" is used to denote what we ended up actually observing. Thus, we want the prediction \hat{Y} to match the actual outcome Y. Y can be categorical (spam/not spam, digits [0-9], letters [A-Z], etc.) or continuous (ratings, prices, profit, etc.).

When the outcome is categorical, we refer to our Machine Learning task as **Classification**. Our predictions will be categorical, just like our outcomes, and will either be *correct* or *incorrect*. When the outcome is continuous, the Machine Learning task is referred to as a **Prediction**. With predictions there is no "right" or "wrong" answers; Due to their continuous nature, we measure the **error** when assessing predictive

algorithms. The error is simply the difference between the prediction and the actual outcome.