

- Geometric Models
- Probabilistic Models
- Logical Models



Geometric Models

In Geometric models, features could be described as points in two dimensions (x- and y-axis) or a three-dimensional space (x, y, and z). Even when features are not intrinsically geometric, they could be modelled in a geometric manner (for example, temperature as a function of time can be modelled in two axes). In geometric models, there are two ways we could impose similarity.

- We could use geometric concepts like lines or planes to segment (classify) the instance space. These are called **Linear models**
- Alternatively, we can use the geometric notion of distance to represent similarity. In this case, if two points are close together, they have similar values for features and thus can be classed as similar. We call such models as **Distance-based models**



Probabilistic Models

Probabilistic models see features and target variables as random variables. The process of modelling represents and manipulates the level of uncertainty with respect to these variables. There are two types of probabilistic models: Predictive and Generative.

- Predictive probability models use the idea of a conditional probability distribution P(Y|X) from which Y can be predicted from X
- Generative models estimate the joint distribution P (Y, X). Once we know the joint distribution for the generative models, we can derive any conditional or marginal distribution involving the same variables

Probabilistic models use the idea of probability to classify new entities Naïve Bayes is an example of a probabilistic classifier.



Logical Models

Logical models use a logical expression to divide the instance space into segments and hence construct grouping models. A logical expression is an expression that returns a Boolean value, i.e., a True or False outcome. Once the data is grouped using a logical expression, the data is divided into homogeneous groupings for the problem we are trying to solve.

There are two types of logical models: Tree models and Rule models.

- **Rule models** consist of a collection of implications or IF-THEN rules. For tree-based models, the 'if-part' defines a segment and the 'then-part' defines the behaviour of the model for this segment. Rule models follow the same reasoning
- **Tree models** can be seen as a particular type of rule model where the ifparts of the rules are organised in a tree structure. Both Tree models and Rule models use the same approach to supervised learning



Groping and Grading Models

- The key difference between grouping and grading models is the way they handle the instance space
- Grouping models
- Grouping models break up the instance space into groups or segments, the number of which is determined at training time
- They have fixed resolution cannot distinguish instances beyond a resolution
- At the finest resolution grouping models assign the majority class to all instances that fall into the segment
- Determine the right segments and label all the objects in that segment



Groping Models

- Tree models repeatedly split the instance space into smaller subsets
- Trees are usually of limited depth and don't contain all the available features
- Subsets at the leaves of the tree partition the instance space with some finite resolution
- Instances filtered into the same leaf of the tree are treated the same, regardless of any features not in the tree that might be able to distinguish them.



Grading Models

- They don't use the notion of segment
- Forms one global model over instance space
- Grading models are (usually) able to distinguish between arbitrary instances, no matter how similar they are
- Resolution is, in theory, infinite, particularly when working in a Cartesian instance space
- Support vector machines and other geometric classifiers are examples of grading models
- They work in a Cartesian instance space
- Exploit the minutest differences between instances

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Groping versus Grading Models

- Some models combine the features of both grouping and grading models
- linear classifiers are a prime example of a grading model
- Instances on a line or plane parallel to the decision boundary can't be distinguished by a linear model
- There are infinitely many segments



Learning Versus Design

- Machine learning is a powerful tool that drives everything from curated content recommendations to optimized user interfaces
- Machine learning answers questions about user behavior
- Machine learning customizes interfaces to users needs
- Digital product designers need to get familiar with machine learning
- Many warn that designers who don't start learning about ML will be left behind. But I haven't seen one that has explored what design and machine learning have to offer each other
- Design and machine learning function like a flywheel: when connected, each provides value to the other. Together, they open up new product experiences and business value
- Design helps machine learning gather better data



Learning Versus Design

- Machine learning is a hungry beast. To deliver the best results, learning algorithms need vast amounts of detailed data, clean of any confounding factors or built-in biases
- Designers can help create user experiences that eliminate noise in data, leading to more accurate and efficient ML-powered applications

Design helps set expectations and establish trust with users