

# INTRO TO DATA SCIENCE

# CLASSIFICATION, LOGISTIC REGRESSION

## **A**GENDA

- Classification Problems
- Logistic Regression
- Evaluating Logistic Regression Models

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# **CLASSIFICATION**

# **CLASSIFICATION VS. CLUSTERING?**

Classification:

Clustering:

# CLASSIFICATION VS. CLUSTERING?

Classification: Supervised

Clustering: Unsupervised

# **CLASSIFICATION**

Predict the value of a categorical response variable

# **CLASSIFICATION**

- Predict the value of a categorical response variable
- Approximate a function that maps an observation to its associated class or label

# **BINARY CLASSIFICATION**

Assign an instance to one of two classes:

- predict whether an image depicts a cat or a dog
- predict whether a tumor is malignant or benign

# **MULTI-CLASS CLASSIFICATION**

Assign an instance to one of more than two classes:

- predict if an image depicts a cat, dog or bird
- predict if a news article should be included in the sports, politics, leisures, or business sections

# **MULTI-LABEL CLASSIFICATION**

Assign instances to one or more of more than two classes:

- predict which of the following tags pertain to a StackOverflow question: Java, Guava, C#, dependency injection, REST, Jersey, Jackson
- predict if a news article should be categorized into multiple classes such as sports and/or current events and/or entertainment

How do we measure how correct a classification model is?

Predict whether tumors are malignant or benign:

- Accuracy: fraction of instances that are classified correctly
  - does not differentiate between malignant tumors that were classified as being benign, and benign tumors that were classified as being malignant.
- In some problems, the costs associated with all types of errors may be the same
- In this problem, failing to identify malignant tumors is likely more severe than failing to identify benign tumors as malignant

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- False negative: a malignant tumor that is incorrectly classifier as being benign

# **CONFUSION MATRIX**

	Prediction		
Actual		1	0
	1	TP	FP
	0	FN	TN

Accuracy is the fraction of instances that were classified correctly

$$ACC = \frac{(TP + TN)}{(TP + TN + FP + FN)}$$

 Precision is the fraction of the tumors that were predicted to be malignant that are actually malignant.

$$P = TP / (TP + FP)$$

 Recall (or True Positive Rate) is the fraction of malignant tumors that the system identified.

$$R = TP / (TP + FN)$$

Fall-out or false positive rate (FPR):

$$FPR = FP / (FP + TN)$$

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# LOGISTIC REGRESSION

Q: What is logistic regression?

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A: A generalization of the linear regression model to *classification* problems.

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In logistic regression, we use a set of covariates to predict probabilities of (binary) class membership.

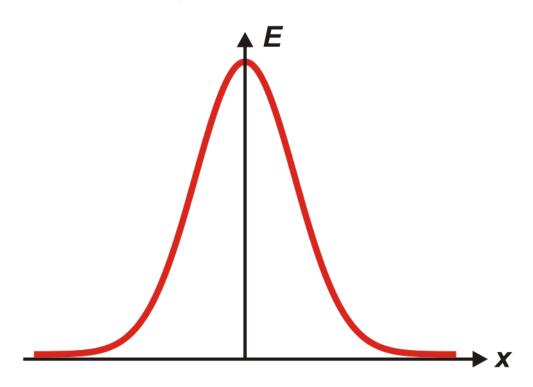
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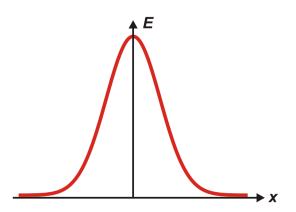
These probabilities are then mapped to class labels, thus solving the classification problem.

 Ordinary linear regression assumes that the response variable is normally distributed.

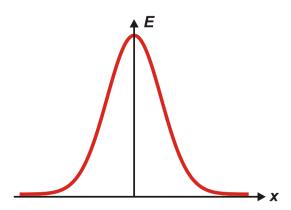
Gaussian distribution, or bell curve



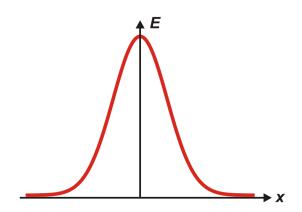
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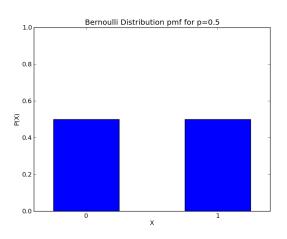


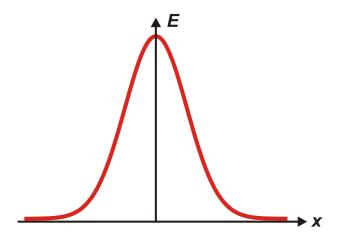
- Describes the probability that an observation will have a value between any two real numbers.
- Normally distributed data is symmetrical.
- The mean, median, and mode of normally distributed data are equal.
- Many natural phenomena approximately follow normal distributions. E.g., the heights of people are normally distributed.

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## RESPONSE VARIABLE DISTRIBUTIONS

- In some problems the response variable is not normally distributed.
- A coin toss can result in two outcomes: heads or tails.
- The Bernoulli distribution describes the probability distribution of a random variable that can take the positive case with probability P or the negative case with probability 1 - P.

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- Linear regression assumes that a constant change in the value of an explanatory variable results in a constant change in the value of the response variable.
- In Logistic regression, the response variable represents a probability that must be constrained to the range {0, 1}.

Suppose we encode a response variable Y as {0=No, 1=Yes}

 Can we simply perform a linear regression of Y on X and classify as "Yes" if Y > 0.5?

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Suppose we encode a response variable Y as {0=No, 1=Yes}

- Can we perform a linear regression of Y on X and simply classify as "Yes" if Y > 0.5?
  - In the case of a binary outcome, linear regression does a decent job as a classifier, and is equivalent to *linear* discriminant analysis
  - However, linear regression might produce probabilities
    P < 0 or P > 1...

Suppose we have a response variable with three possible values. A patient arrives at the emergency room, and we must classify them according to their symptoms.

$$Y = \begin{cases} 1, & \text{stroke} \\ 2, & \text{drug OD} \\ 3, & \text{heart attack} \end{cases}$$

This encoding implies that the difference between stroke and drug overdose is the same as between drug overdose and heart attack

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- Ordinary linear regression is a special case of the generalized linear model that relates a linear combination of the explanatory variables to a normally-distributed response variable using the *identity link function*.
- We can use a different link function to relate a linear combination of the explanatory variables to response variable that is not normally-distributed.

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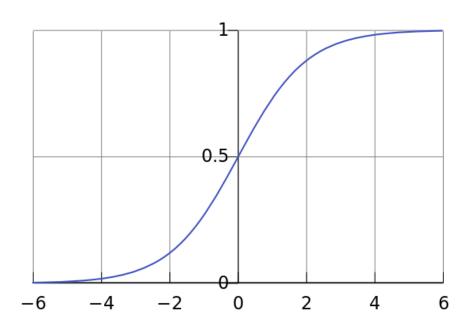
- Logistic regression regresses the probability that an instance is the positive case onto the explanatory variables.
- Models the conditional probability P(Y = 1 | X)
- If the response variable is equal to or exceeds a discrimination threshold the positive class is predicted; otherwise, the negative class is predicted.
- The response variable is modeled as a function of a linear combination of the explanatory variables using the logistic function.

 The logistic function always returns a value between zero and one.

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$$F(x) = \frac{1}{1 + e^{-(\beta_0 + \beta x)}}$$

The **logit function** is the inverse of the logistic function. It links back to a linear combination of the explanatory variables so that the parameter values can be solved.

$$F(x) = \frac{1}{1 + e^{-(\beta_0 + \beta x)}}$$

$$g(x) = \ln \frac{F(x)}{1 - F(x)} = \beta_0 + \beta x$$

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# PRACTICE