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程序代写代做 CS编程辅导

Introduction to Machine Learning

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Developed by Prajwol Sangat
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Last week

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Parallel Aggregation
- Parallel Sort
- Parallel Group-By

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This week

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What is Machine Le
Machine Learning B
Types of Machine Learning
Feature Engineering

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According to McKinsey study, 35% of what consumers purchase on Amazon and 75% of what they watch on Netflix is driven by machine learning–based product recommendations.

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What is Machine Learning?

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What is Machine Learning?

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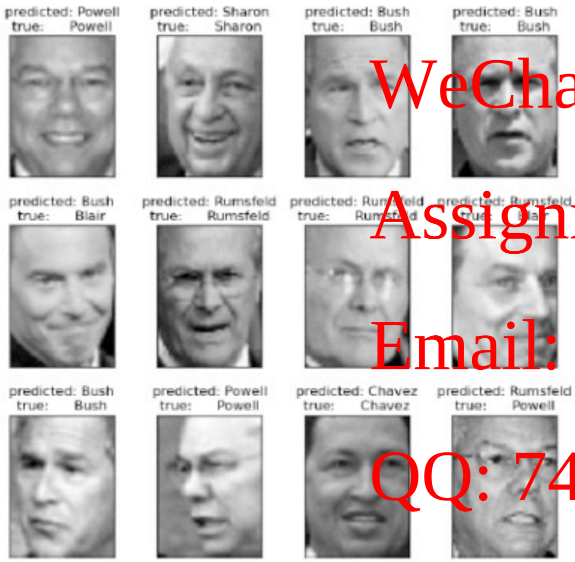
A computer program is said to learn fr[...] *E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as m*[...]*nproves with experience E*", (Tom Mitchell, 1997)

Face recognition



Experience E	Task T	Performance P
databases of thousands of known faces	given a new photo, recognise the name of the face	how accurate the recognition is

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Examples

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Watson, Ken Jennings, and Brad Rutter in their *Jeopardy!* exhibition match.

Detecting Spam Emails

Detect credit card fraud

[illegible]e E	Task T	Performance P
[illegible] of [illegible]nswer pairs	given an question, find the best answer	how accurate the answer is
Examples of spam emails and not-spam email	To assign a label "spam" or "not-spam" to an email	how accurate spam email can be detected
Data collected for credit-card transactions deemed as fraud and not-fraud	To assign a label 'fraud' or "not fraud" to a given credit-card transaction	how accurate a credit-card fraud transaction can be detected.

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Elements of machine learning

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① Data

feature $x \in \mathbb{R}^d$
label $y \in Y$

Dataset $\mathcal{D} = \{x_i, y_i\}_{i=1}^{n}$

el

$: X \to Y$

Y is label space
θ: model parameter

③ Assessment

How well is f_θ doing w.r.t data $\mathcal{D}$?

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Data processing

feature extraction, feature selection, feature transformation, feature reduction, feature scaling, feature normalization

Predictive Model $Y = f_\theta(X)$

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Model Learning (Training)

- Find an optimal model f_θ (by estimating model parameters θ) using training data
- Based on loss function (e.g., minimize error between true and predicted labels)

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Model Testing $\hat{y} = f_\theta(x_{test})$

- Test the learned model in predicting unseen test data
- Performance metrics to assess model accuracy

Illustration: Linear Regression model

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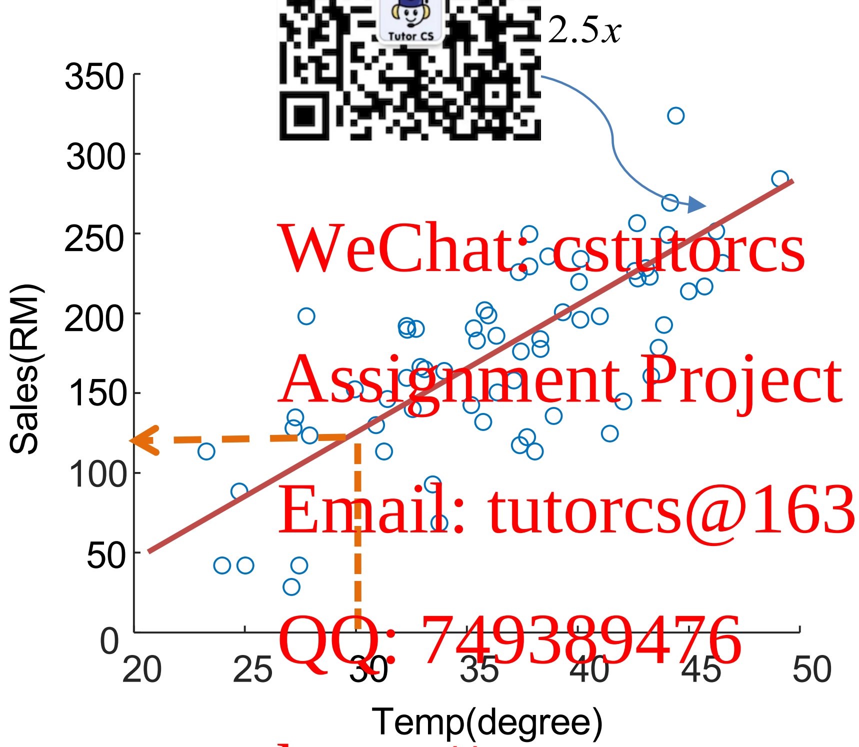
Problem: Predict ice cream sales g[illegible]ature

Data

Day	Temp	Sales
i	x_i	y_i
1	36	200
2	31	100
3	24	50
⋮	⋮	
100	38	250



Predictive Model:

- What is good model *f*(.) to maps *x* to *y*?

$$f(x) = \theta_o + \theta_1 x$$

Model Learning/Estimation:

- How to choose parameters θ_o, θ_1 ?
  - ❑ Define loss function
  - ❑ Estimate using learning algorithm

Estimated parameters: $\theta_o = 50, \; \theta_1 = 2.5$

Prediction:

- Given new input, predict *y* with learned model $\hat{y} = f(x_{new}) = \theta_o + \theta_1 x_{new}$

Predicted output $\hat{y} = 50 + 2.5(30) = 125$

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Overview of machine learning

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...odel θ
...ata

Training Data
$D_{train}=\{x_i, y_i\}_{i=1}^{n}$

...orithm

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Training Stage

Test Data
x_{test}

Learned Predictive Model
$Y = f_\theta(X)$

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Predicted Label
$\hat{y} = f_\theta(x_{test})$

Classification /Prediction Stage

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$f_\theta(.)$ *maps X to Y*

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Assessment of prediction performance

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Data

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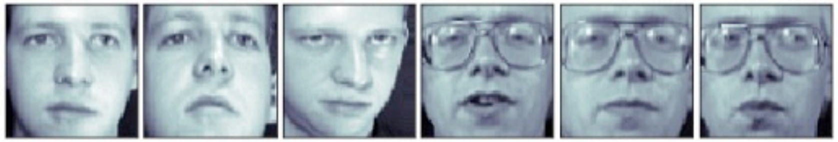
Features: x_i

- a set of attributes, each is a vector or matrix.
- E.g., represent each email as a bag-of-word vector (features) into a real-valued matrix.

data points ... $\{x_i\}$



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Labels: y_i

- values, categories, classes, assigned to data points.
- E.g., 0 = non-spam, 1 = spam;

data points with labels ... $\{x_i, y_i\}$

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Data points (aka instances, samples) $\{x_i\}$ or $\{x_i, y_i\}$

- these are items or instances of data used for training and evaluating ML models.
- E.g., labelled emails in spam detection; transaction data in credit card fraud detection; a photo in face recognition.

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$$\begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 1 & \cdots & 0 \\ & & \cdots & \\ 0 & 0 & \cdots & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 2 & \cdots & 0 \\ & & \cdots & \\ 0 & 0 & \cdots & 1 \end{bmatrix}$$

x_i features

y_i 0 = Jack, 1 = John, etc ...

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Dataset with n samples: $\mathcal{D} = \{x_i, y_i\}_{i=1}^{n}$

Machine Learning: Data Types

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- **Vector**
  - A mathematical
  - *dense vectors*, where every entry is stored, and
  - *sparse vectors*, where only the nonzero entries are stored to save space.
- **Labeled Point**
  - A labeled data point for supervised learning algorithms such as classification and regression.
  - Includes a feature vector and a label (which is a floating point value).

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Machine Learning: Data Types

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Vector

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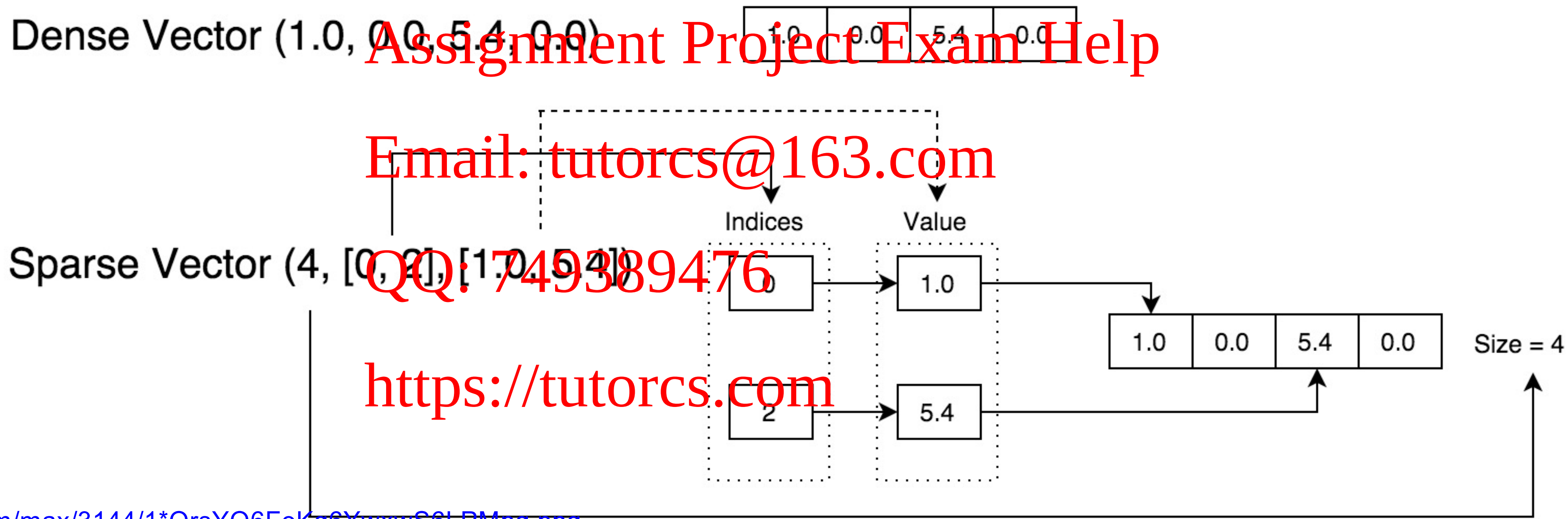

https://miro.medium.com/max/3144/1*OrsYQ6FoKq6YwxwS6LPMpg.png

Features

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All learning algorithms require defining a set of *features* for each item, which will be fed into the learning function.

- *For example, for an email, some features might include the server it comes from, or the number of mentions of the word free, or the color of the text.*

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In many cases, defining the right features is the most challenging part of using machine learning.

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- *For example, in a product recommendation task, simply adding another feature (e.g., realizing that which book you should recommend to a user might also depend on which movies she's watched) could give a large improvement in results.*

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Machine Learning Fundamentals

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Supervised and Unsupervised Models

Bias and Variance

Underfitting and Overfitting

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Model: Types of Model Learning

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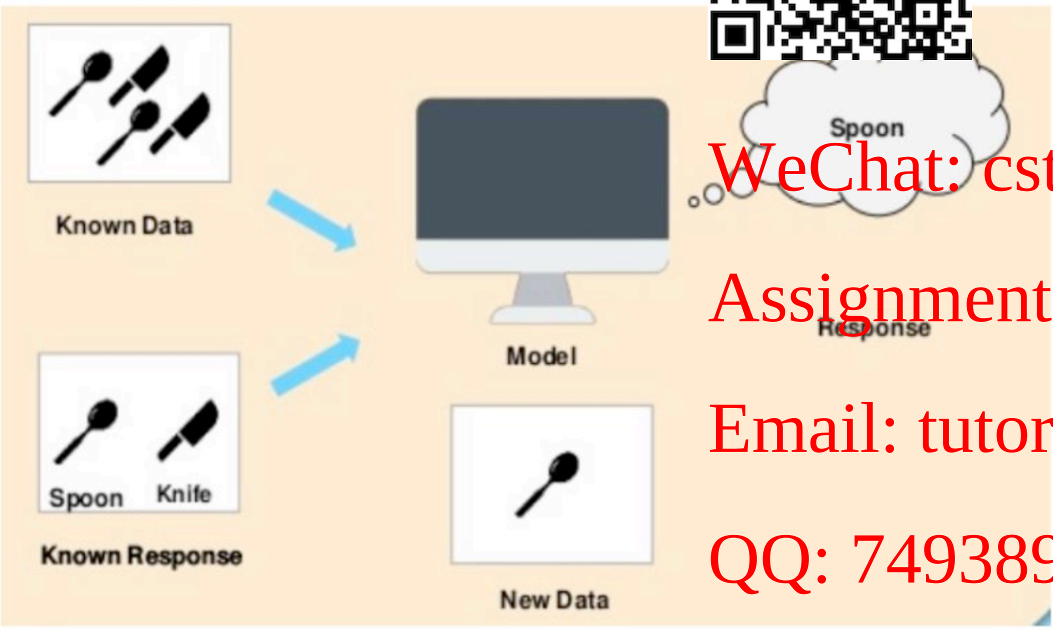
Supervised

Unsupervised



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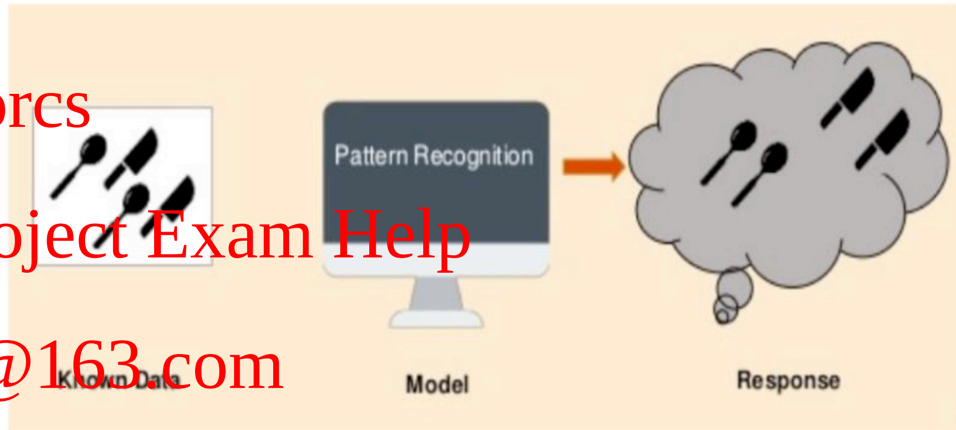

https://www.simplilearn.com/tutorials/machine-learning-tutorial/supervised-and-unsupervised-learning

Types of Model Learning: Supervised

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- Goal: Learn a funct[illegible]abelled training data to predict the output label(s) give[illegible]unlabeled input.

- Training data consists of input features and output information (labels)

- Two types of supervised learning:
  - ❑ Classification
  - ❑ Regression

Data: $(x_1, y_1), \ldots, (x_n, y_n)$

Function: $f: X \rightarrow Y$

x = feature
y = a discrete label (classification),
y = a continuous value (regression)

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Supervised Machine Learning: Classification

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Classification problem: To s… puts into a discrete set of classes or labels.

- Binary classification
- Multinomial (Multi-cl… cation

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Binary classification example: dog or not dog

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Supervised Machine Learning: Classification

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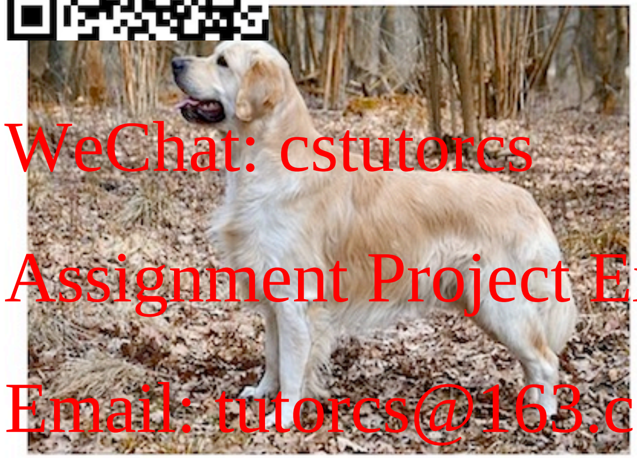

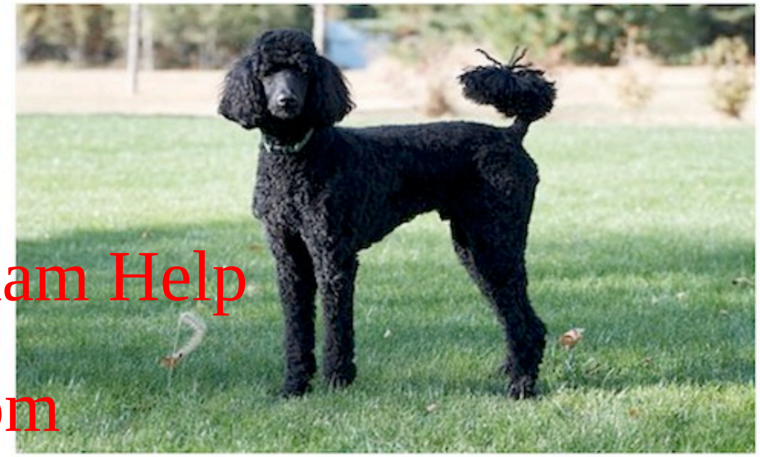

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Multinomial classification example: Australian shepherd, golden retriever, or poodle

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Supervised Machine Learning: Regression

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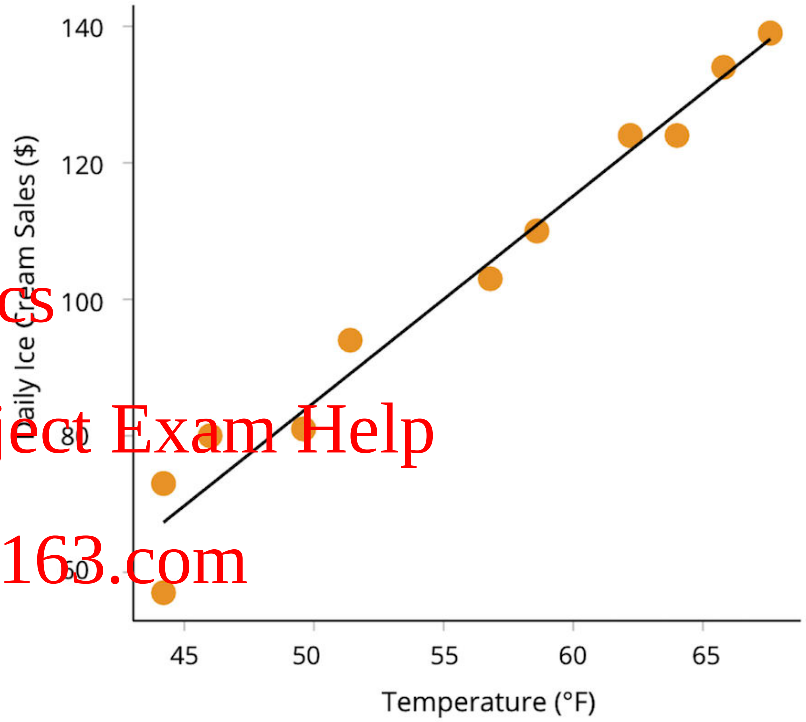
- A regression pro when the output e is a real value, such as “dollars” or “weight”.



Regression example: predicting ice cream sales based on temperature

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Supervised Machine Learning in Apache Spark

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Algorithm	Typical usage
Linear regression	Regression
Logistic regression	Classification (we know, it has regression in the name!)
Decision trees	Both
Gradient boosted trees	Both
Random forests	Both
Naive Bayes	Classification
Support vector machines (SVMs)	Classification

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Types of Model Learning: Unsupervised

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- Goal: Explore the ur structure of the data to extract meaningful informat ut guidance of known output info.
- Deals with unlabelled data (no output labels)
- Two types of unsupervised learning:
  - ❑ Clustering
  - ❑ Association

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Unsupervised Machine Learning: Clustering

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- Clustering problem: Div… …to clusters which are simil… …n them and are dissimilar … …a belonging to another cluster.
- Where you want to discover the inherent groupings in the data, eg grouping customers by purchasing behaviour

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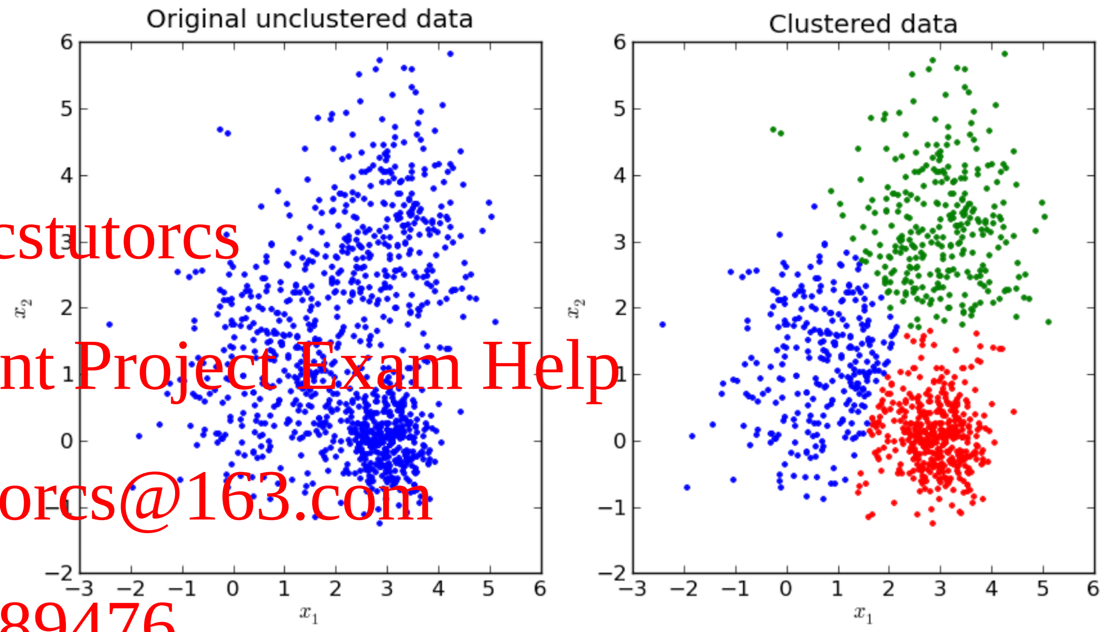

Clustering example

Unsupervised Machine Learning: Association

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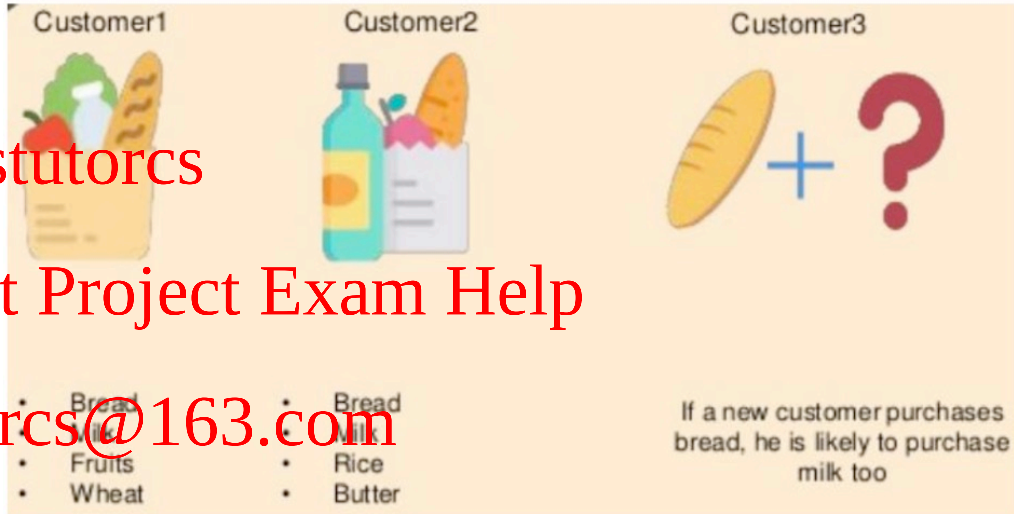
- Association rule learning
  Discover the probability of occurrence (association) between items in a large dataset

- Where you want to discover rules that describe large portions of your data, e.g., people who buy X also tend to buy Y.



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Unsupervised Machine Learning in Apache Spark

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- *k*-means,
- Latent Dirichlet Allocation (LDA), and
- Gaussian mixture models.

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Machine Learning: Assessment

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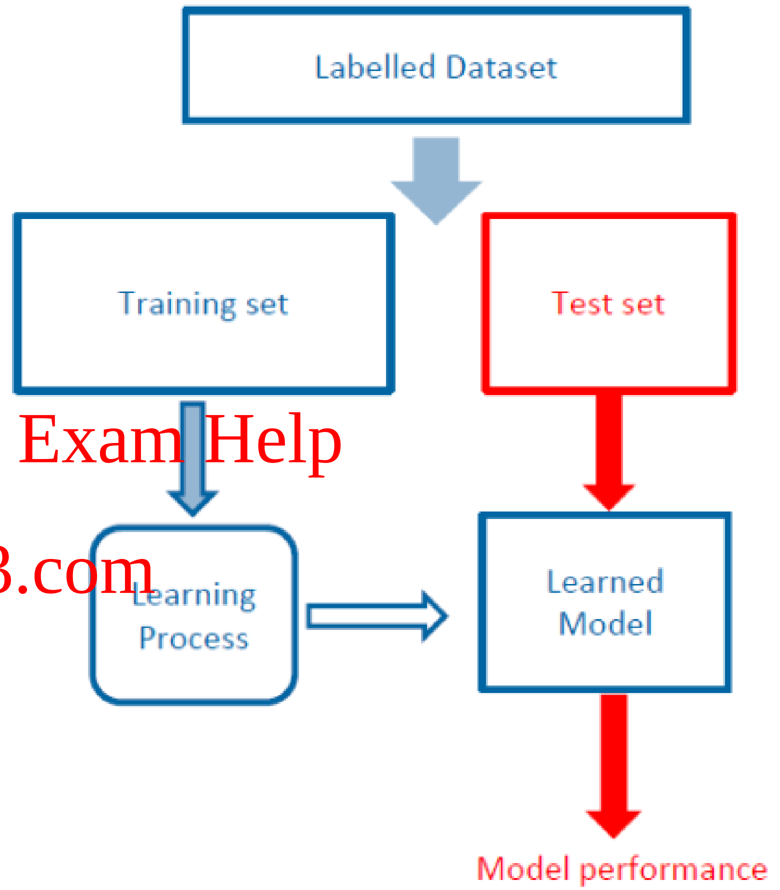
How to prepare the data?

- Train-Test split
- K-fold cross-validation

How to measure performance?

- TP, FP, TN, FP, confusion matrix
- Accuracy, Recall, Precision, F1-score



Machine Learning: Performance Metrics

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Example: Email Spam Detect

In test set: 10 spam, 20 non-sp

Positive = spam

True labels

Predicted labels	SPAM (1)	NON-SPAM (0)
SPAM (1)	7	5
NON-SPAM (0)	3	15

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actual class

predicted class	positive	negative
positive	true positives (TP)	false positives (FP)
negative	false negatives (FN)	true negatives (TN)

$$\text{Accuracy} = \frac{tp + tn}{tp + tn + fp + fn}$$

$$\text{Precision} = \frac{tp}{tp + fp}$$

$$\text{Recall} = \frac{tp}{tp + fn}$$

$$F = 2 \cdot \frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

Machine Learning: Bias and Variance

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Bias is the gap between the averaged predicted value by the model and the actual value of the data.

Variance measures the distance of the predicted values in relation to each other.

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Machine Learning: Bias and Variance

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Machine Learning: Overfitting and Underfitting

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Overfitting (high var[illegible]w bias) is a model that performs well on the training data [illegible]ralizes poorly to any new data.

Underfitting (low variance, high bias) is an overly simple model that does not perform well even on the training data.

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- **Preventing Overfitting**
  - **Train with more data**

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Machine Learning: Overfitting and Underfitting

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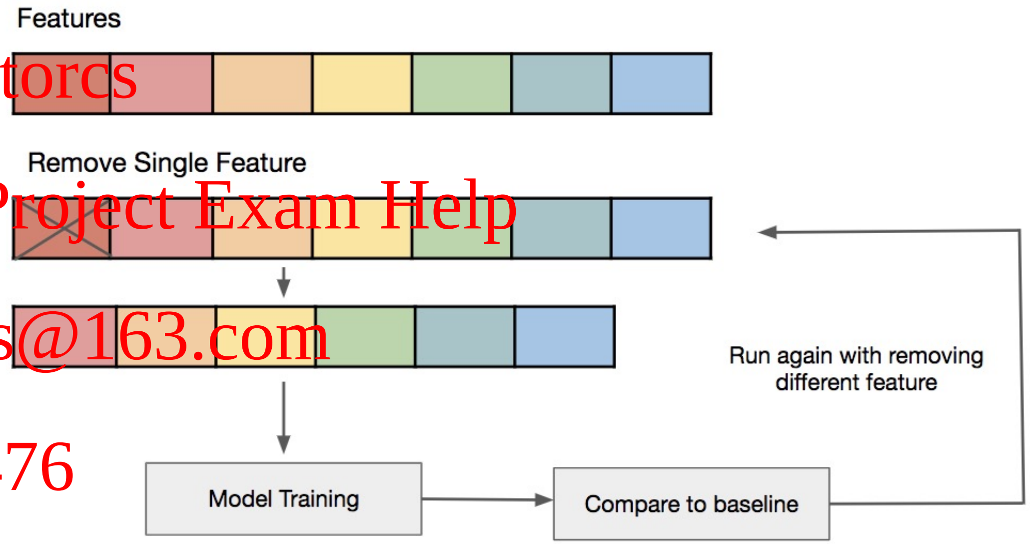
- **Preventing Overfitting**
  - **Train with more data**
  - **Remove features**



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- **Preventing Overfitting**
  - **Train with more data**
  - **Remove features**
  - **Early stopping**

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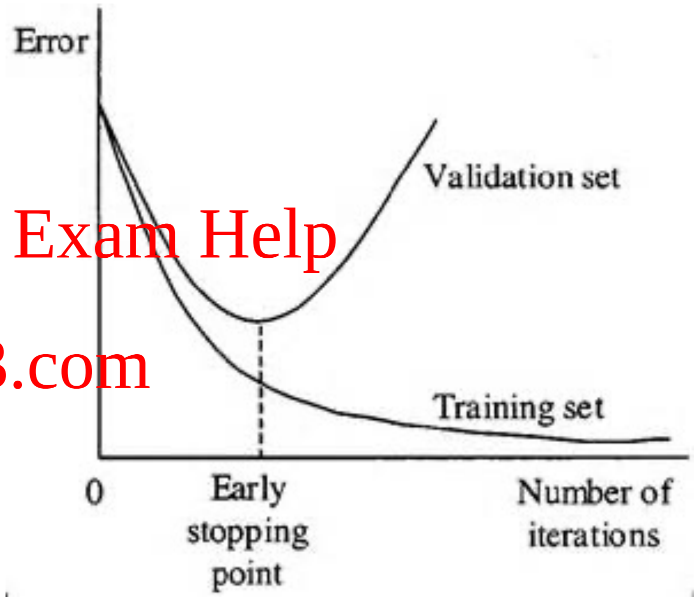

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- **Preventing Overfitting**
  - Train with more data
  - Remove features
  - Early stopping
  - Cross validation

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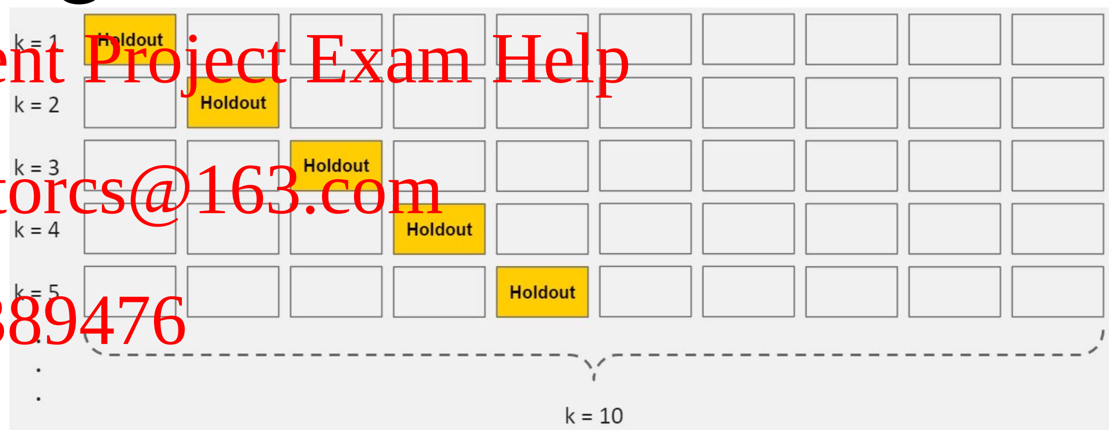
K-Fold Cross-Validation



To be continued..

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Next topic -> Featurizatio

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Machine Learning: Pipeline

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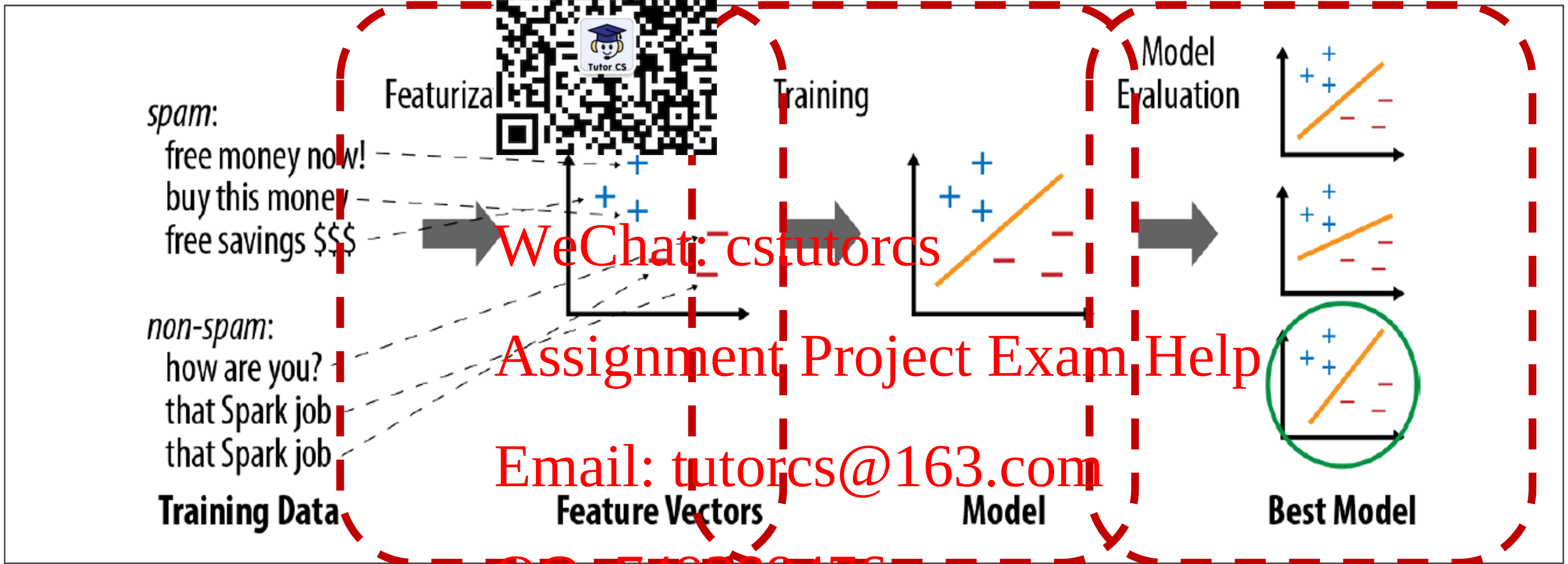

Figure 11-1. Typical steps in a machine learning pipeline

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Machine Learning: Pipeline

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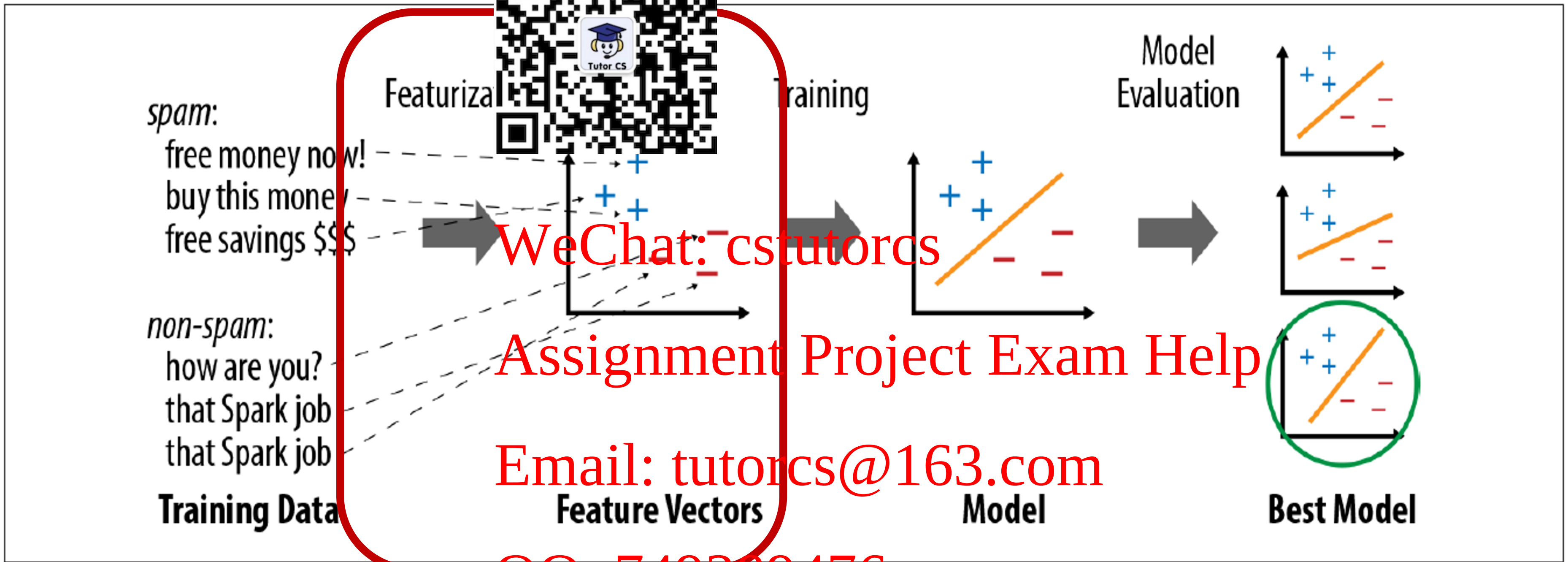

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Figure 11-1. Typical steps in a machine learning pipeline

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Featurization: Extraction, transformation and selection

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Extraction
- Extracting featu[illegible]raw” data

Transformation
- Scaling, converting, or modifying features

Selection
- Selecting a subset from a larger set of features

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Featurization: Feature Extraction and Transformation

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Features

– Any machine learni[illegible]n requires some training data. In training data we have value[illegible]ures for all historical records. Consider this simple data set

Height	Weight	Age	Class
165	70	22	Male
160	58	22	Female

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– We can prepare training data by following two techniques

Feature Extraction

Feature Selection

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Featurization: Feature Extraction and Transformation

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Feature extractors

- CountVectorizer
- TF-IDF
- Word2Vec
- FeatureHasher (in tutorial)

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Featurization: Feature Extractors

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Count Vectorizer

- Convert a collection of text documents to vectors of token counts.
- During the fitting process, *Count Vectorizer* will select the top *vocabSize* words ordered by term frequency across the corpus.

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```
 id | texts
----|----------------------------------
 0  | Array("a", "b", "c")
 1  | Array("a", "b", "b", "c", "a")
```

Featurization: Feature Extractors

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Term Frequency–I[illegible]ocument Frequency, or TF-IDF,

- A simple way t[illegible]e feature vectors from text documents (e.g., web pages).
- It computes two statistics for each term in each document:

  The term frequency (TF), which is the number of times the term occurs in that document, and

  The inverse document frequency (IDF), which measures how (in)frequently a term occurs across the whole document corpus.

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Featurization: Feature Extractors

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Term Frequency–Inverse Document Frequency, or TF-IDF,

- Denote a term by *t*, a document by ***d***, and the corpus by ***D***.

- Term frequency ***TF(t,d)*** is the number of times that term ***t*** appears in document ***d***, while document frequency ***DF(t,D)*** is the number of documents that contains term ***t***.

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- Inverse document frequency is a numerical measure of how much information a term provides:

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$$IDF(t, D) = \log \frac{|D| + 1}{DF(t, D) + 1},$$

where **|D|** is the total number of documents in the corpus.

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Featurization: Feature Extractors

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Term Frequency–I[illegible]ocument Frequency, or TF-IDF,

- The product of th[illegible]s, TF × IDF, shows how relevant a term is to a specific docum[illegible]t is common in that document but rare in the whole corpus).
- The TF-IDF measure is simply the product of TF and IDF:

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$$TFIDF(t,d,D) = TF(t,d) \cdot IDF(t,D).$$

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Featurization: Feature Extractors

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Term Frequency–Inverse Document Frequency, or TF-IDF,

Suppose that we have term count tables of a corpus consisting of only two documents, as listed on the right.

Calculate TF-IDF for the term "this".

Document 1

Term	Term Count
this	1
is	1
a	2
sample	1

Document 2

Term	Term Count
this	1
is	1
another	2
example	3

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TF-IDF (Solution),

Calculating TF for “thi

TF (“this”, d1) = 1/5 = 0.2
TF (“this”, d2) = 1/7 = 0.14
(Approx.)

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Document 1

Term	Term Count
this	1
is	1
a	2
sample	1

Document 2

Term	Term Count
this	1
is	1
another	2
example	3

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TF-IDF (Solution),

Calculating IDF for “th

|D| = 2

DF(t, D) = 2

IDF (“this”, D) = log (3/ 3) = 0

Document 1

Term	Term Count
this	1
is	1
a	2
sample	1

Document 2

Term	Term Count
this	1
is	1
another	2
example	3

$$IDF(t, D) = \log \frac{|D| + 1}{DF(t, D) + 1},$$

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TF-IDF (Solution),

Calculating TF-IDF for “thi

TF-IDF (“this”, d1, D) = 0.2 * 0 = 0

TF-IDF (“this”, d2, D) = 0.14 * 0 = 0

Document 1

Term	Term Count
this	1
is	1
a	2
sample	1

Document 2

Term	Term Count
this	1
is	1
another	2
example	3

$$TFIDF(t,d,D) = TF(t,d) \cdot IDF(t,D).$$

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Exercise: Calculate [illegible] for the term “example”.

Document 1

Term	Term Count
this	1
is	1
a	2
sample	1

Document 2

Term	Term Count
this	1
is	1
another	2
example	3

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Word2Vec

- maps each word [illegible] e fixed-size vector.
- transforms each document into a vector using the average of all words in the document.
- this vector can then be used as features for prediction, **document similarity calculations**, etc.

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Home Work: Do some research and write a program to find the document similarity using Word2Vec.

Featurization: Extraction, transformation and selection

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Extraction
- Extracting featu[illegible]raw” data

Transformation
- Scaling, converting, or modifying features

Selection
- Selecting a subset from a larger set of features

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Featurization: Feature Extraction and Transformation

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Feature Transform

- Tokenization
- Stop Words Re
- String Indexing
- One Hot Encoding
- Vector Assembler (Implement In tutorial)

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Featurization: Feature Transformers

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Tokenization

- It is the process [illegible] text (such as a sentence) and breaking it into individual terms (usually words).

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Text

“The cat sat on the mat.”

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↓

Tokens

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“the”, “cat”, “sat”, “on”, “the”, “mat”, “.”

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Featurization: Feature Transformers

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Stop Words are wo… should be excluded from the input, typically because th… appear frequently and don't carry as much meaning.

Some words contain more information than others

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stopwords — [the, in, for, you, will, have, be]

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Quiz: How many words will be removed when we remove stopwords from "Hi Katie the machine learning class will be great best Sebastian"

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Featurization: Feature Transformers

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Stop Words Remover

Takes as input a sequence of strings (e.g. the output of a Tokenizer)

Drops all the stop words from the input sequences.

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```
id | raw                           | filtered
----|-----------------------------|--------------------
0   | [I, saw, the, red, balloon]  |  [saw, red, balloon]
1   | [Mary, had, a, little, lamb]|[Mary, little, lamb]
```

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Featurization: Feature Transformers

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String Indexing

Encoding a string column of labels to a column of label indices.

```
id | category | categoryIndex
----|----------|--------------
0  | a        | 0.0
1  | b        | 2.0
2  | c        | 1.0
3  | a        | 0.0
4  | a        | 0.0
5  | c        | 1.0
```

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Featurization: Feature Transformers

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One Hot Encoding

Maps a categorical feature represented as a label index to a binary vector..

A single one-value indicates the presence of a specific feature value from among the set of all feature values.

For string type input data, it is common to encode categorical features using String Indexing first.

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Featurization: Feature Transformers

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Why One Hot Enco

For categorical when there is no ordinal relationship, the string indexing is not enough...

Using this encoding and allowing the model to assume a natural ordering between categories may result in poor performance or unexpected results.

A one-hot encoding can be applied to the integer representation. This is where the integer encoded variable is removed and a new binary variable is added for each unique integer value.

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Why One Hot Enco

Example: Let's s ve 3 data instances with attributes of **Preferred Progra anguage** and **OS of Choice.**

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Preferred Programming Language	OS of Choice
Javascript	OSX
Python	Linux
Scala	OSX

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Featurization: Feature Transformers

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Why One Hot Enco

Preferred Programming Language	OS of Choice
Javascript	OSX
Python	Linux
Scala	OSX

String Indexing

Preferred Programming Language	OS of Choice
0	0
1	1
2	0

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Featurization: Feature Transformers

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- **Why cant we ST[illegible]e?**

The Problem Of Or[illegible]

Machine learning algorithms treat the ordinality of numbers in an attribute with some significance: *a higher number "must be better" than a lower number*.

String Indexing

Preferred Programming Language	OS of Choice
0	0
1	1
2	0

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程序代写代做 CS编程辅导

Featurization: Feature Transformers

- **String Indexing**

Preferred Programming Language	OS of Choice
0	0
1	1
2	0

- **One Hot Encoding**

Javascript	Python	Scala	OSX	Linux
1	0	0	1	0
0	1	0	0	1
0	0	1	1	0

Homework: Have a look at [Principal Component Analysis (PCA)]

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Featurization: Feature Transformers

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Why One Hot Encoding

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Featurization: Extraction, transformation and selection

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- Extracting featu raw” data

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Featurization: Feature Selectors

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Feature selection

- This process tri[illegible] most important features that are contributing to decide the label.

Vector Slicer

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- It takes a feature vector and outputs a new feature vector with a sub-array of the original features.

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- It is useful for extracting features from a vector column.

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```
 userFeatures      | features
-------------------|--------------
 [0.0, 10.0, 0.5]  | [10.0, 0.5]
```

Lecture Demo

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Spam Classification [illegible]

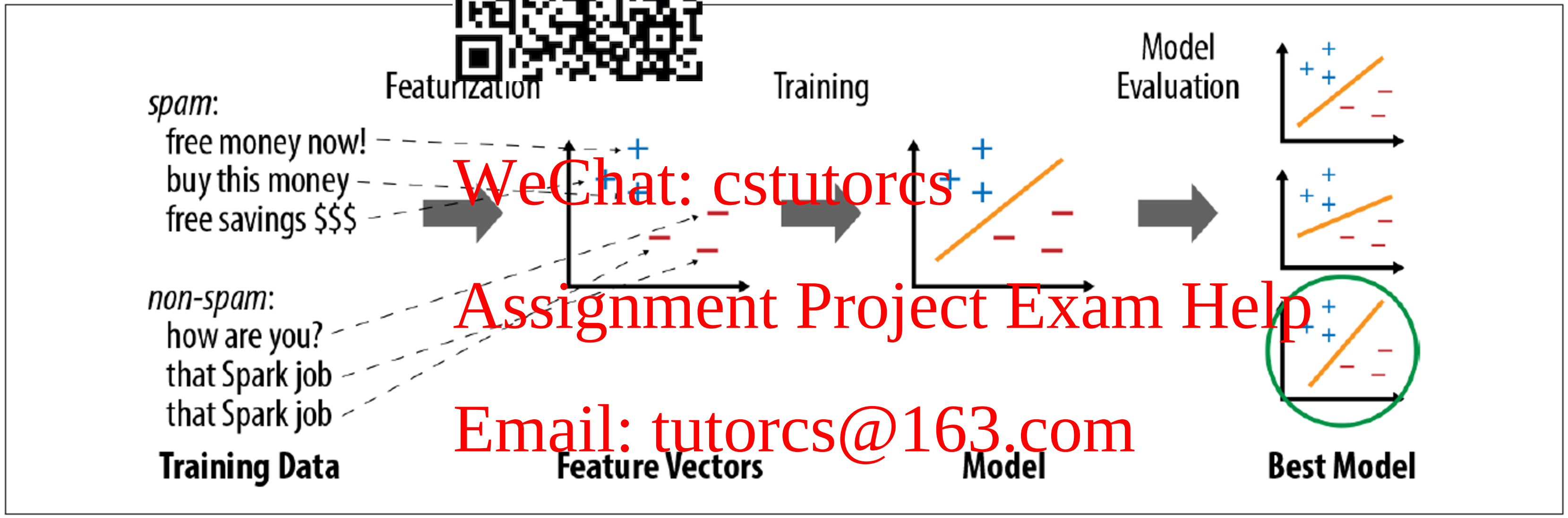

Figure 11-1. Typical steps in a machine learning pipeline

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Thank You

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