Machine Learning - Classification

Professor Widom's Instructional Odyssey

www.professorwidom.org

Stanford University

Google

Instabase

Google Cloud Platform

Association for Computing Machinery

Very Large Data Bases Endowment Inc.

amazon web services

Data Tools and Techniques

- Basic Data Manipulation and Analysis
  Performing well-defined computations or asking well-defined questions (“queries”)
- Data Mining
  Looking for patterns in data
- Machine Learning
  Using data to build models and make predictions
- Data Visualization
  Graphical depiction of data
- Data Collection and Preparation

Regression

Using data to build models and make predictions

- Supervised
- Training data, each example:
  - Set of predictor values - "independent variables"
  - Numerical output value - "dependent variable"
- Model is function from predictors to output
  - Use model to predict output value for new predictor values
- Example
  - Predictors: mother height, father height, current age
  - Output: height

Classification

Using data to build models and make predictions

- Supervised
- Training data, each example:
  - Set of feature values – numeric or categorical
  - Categorical output value - "label"
- Model is method from feature values to label
  - Use model to predict label for new feature values
- Example
  - Feature values: age, gender, income, profession
  - Label: buyer, non-buyer

Other Examples

Medical diagnosis

- Feature values: age, gender, history, symptom1-severity, symptom2-severity, test-result1, test-result2
- Label: disease

Email spam detection

- Feature values: sender-domain, length, #images, keyword_1, keyword_2, …, keyword_n
- Label: spam or not-spam

Credit card fraud detection

- Feature values: user, location, item, price
- Label: fraud or okay

Algorithms for Classification

Despite similarity of problem statement to regression, non-numerical nature of classification leads to completely different approaches

- K-nearest neighbors
- Decision trees
- Naïve Bayes
- Deep neural networks
- … and others

K-Nearest Neighbors (KNN)

For any pair of data items i_1 and i_2, from their feature values compute *distance*(i_1,i_2)

Example:

Features - gender, profession, age, income, postal-code

person$_1$ = (male, teacher, 47, $25K, 94305)
person$_2$ = (female, teacher, 43, $28K, 94309)

distance(person$_1$, person$_2$)

distance() can be defined as inverse of *similarity*()

K-Nearest Neighbors (KNN)

Features - gender, profession, age, income, postal-code

person_1 = (male, teacher, 47, $25K, 94305)

person_2 = (female, teacher, 43, $28K, 94309)

Remember training data has labels

K-Nearest Neighbors (KNN)

Features - gender, profession, age, income, postal-code

$person_1$ = (male, teacher, 47, \$25K, 94305) buyer

$person_2$ = (female, teacher, 43, \$28K, 94309) non-buyer

Remember training data has labels

To classify a new item *i* : In the labeled data find the K closest items to *i*, assign most frequent label

$person_3$ = (female, doctor, 40, \$40K, 95123)

KNN Example

- City temperatures – France and Germany
- Features: longitude, latitude
- Distance is Euclidean distance

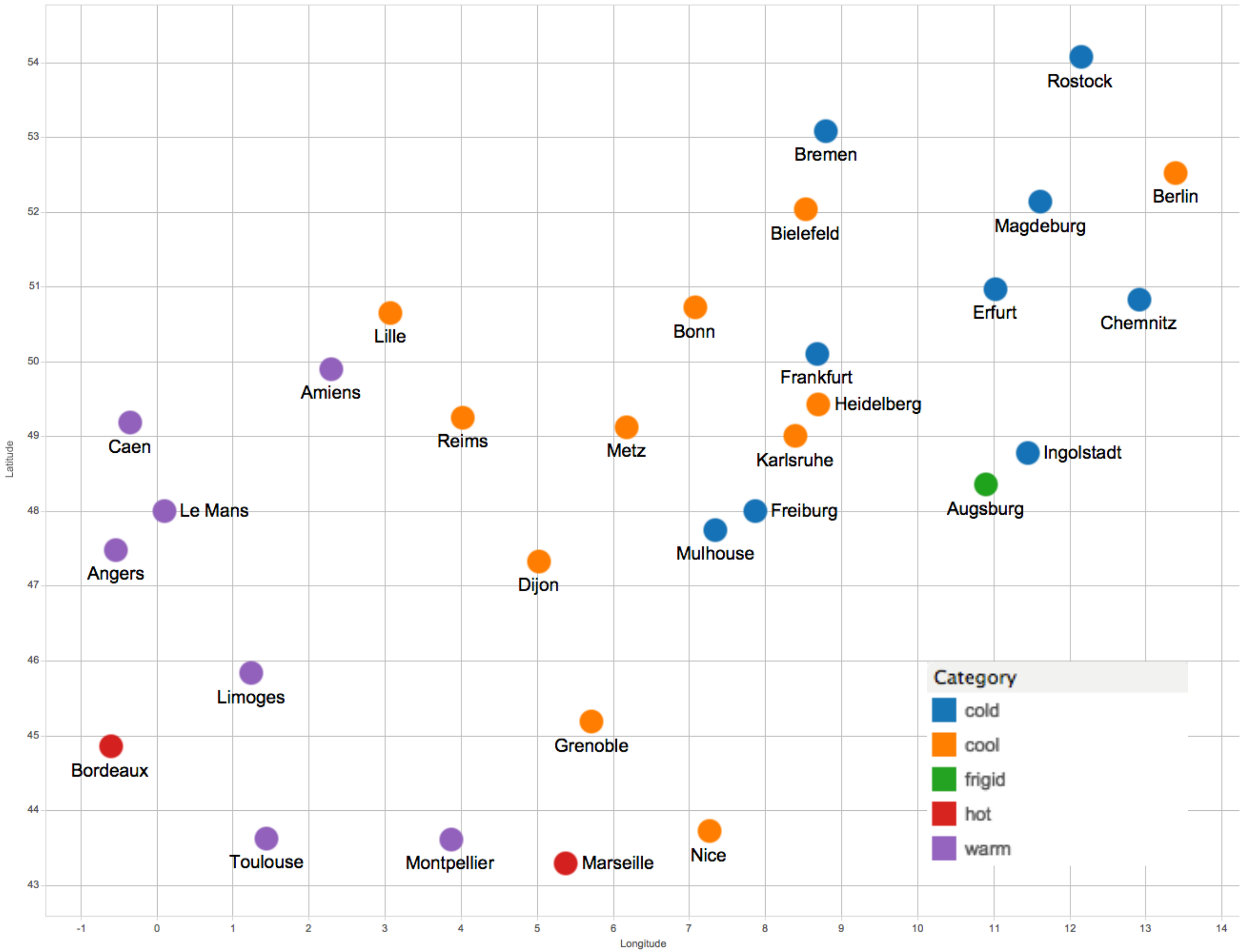
  $distance([o_1,a_1],[o_2,a_2]) = sqrt((o_1-o_2)^2 + (a_1-a_2)^2)$

  = actual distance in x-y plane
- Labels: frigid, cold, cool, warm, hot

Nice (7.27, 43.72) cool
Toulouse (1.45, 43.62) warm
Frankfurt (8.68, 50.1) cold
......

Predict temperature category from longitude and latitude

KNN Example



Rostock
Bremen
Berlin
Bielefeld
Magdeburg
Erfurt
Chemnitz
Lille
Bonn
Frankfurt
Amiens
Heidelberg
Caen
Reims
Metz
Karlsruhe
Ingolstadt
Augsburg
Le Mans
Freiburg
Mulhouse
Angers
Dijon
Limoges
Grenoble
Bordeaux
Toulouse
Montpellier
Marseille
Nice
Category
cold
cool
frigid
hot
warm
Latitude
Longitude

KNN Summary

To classify a new item *i* : find K closest items to *i* in the labeled data, assign most frequent label

- No hidden complicated math!
- Once distance function is defined, rest is easy
- Though not necessarily efficient

  Real examples often have thousands of features

  - Medical diagnosis: symptoms (yes/no), test results
  - Email spam detection: words (frequency)

  Database of labeled items might be enormous

“Regression” Using KNN

Features - gender, profession, age, income, postal-code

$person_1$ = (male, teacher, 47, $25K, 94305) buyer

$person_2$ = (female, teacher, 43, $28K, 94309) non-buyer

Remember training data has labels

To classify a new item *i*, find K closest items to *i* in the labeled data, assign most frequent label

$person_3$ = (female, doctor, 40, $40K, 95123)

"Regression" Using KNN

Features - gender, profession, age, income, postal-code

person$_1$ = (male, teacher, 47, \$25K, 94305) \$250

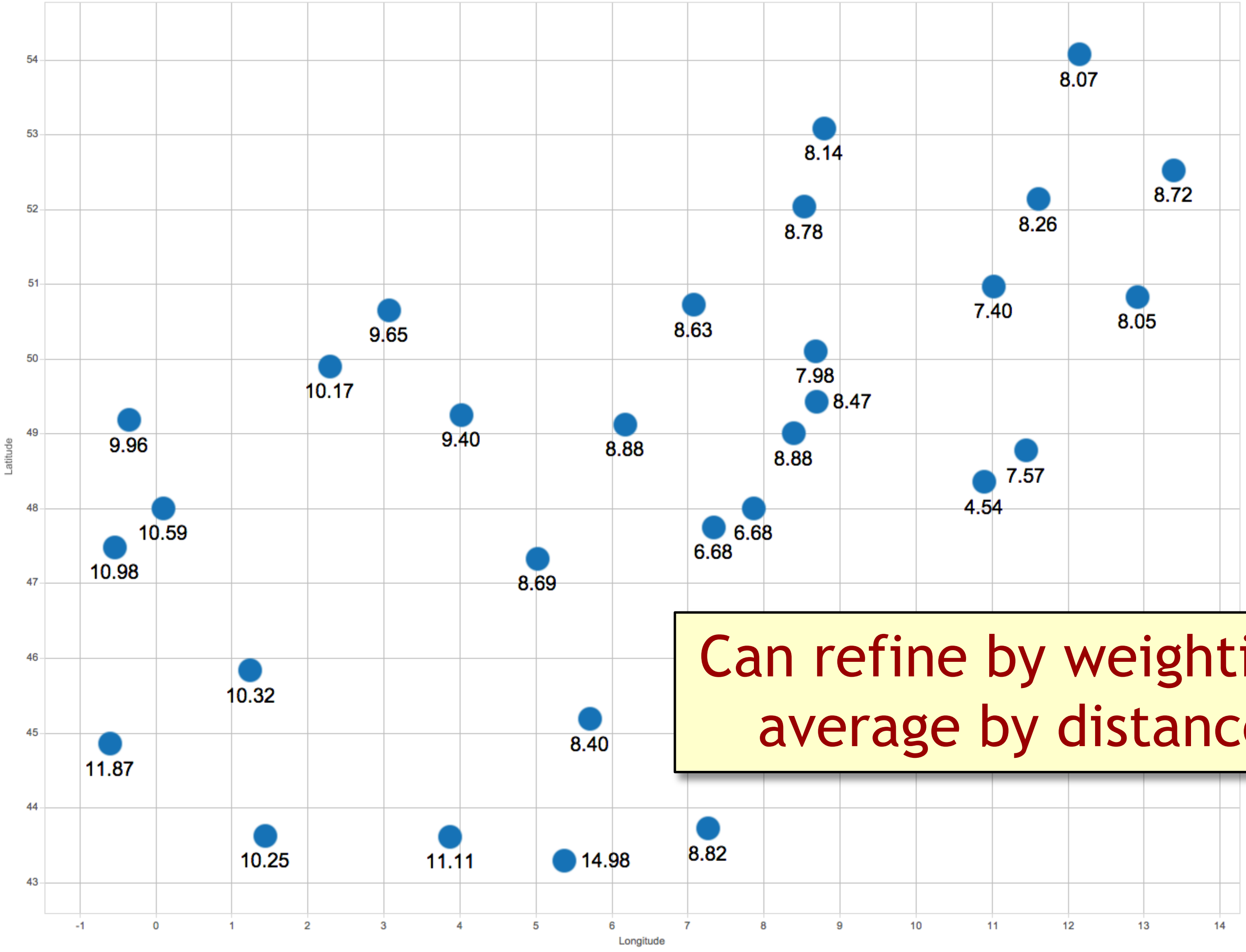
person$_2$ = (female, teacher, 43, \$28K, 94309) \$100

Remember training data has labels

To classify a new item *i*, find K closest items to *i* in the labeled data, assign average value of labels

person$_3$ = (female, doctor, 40, \$40K, 95123)

Regression Using KNN - Example



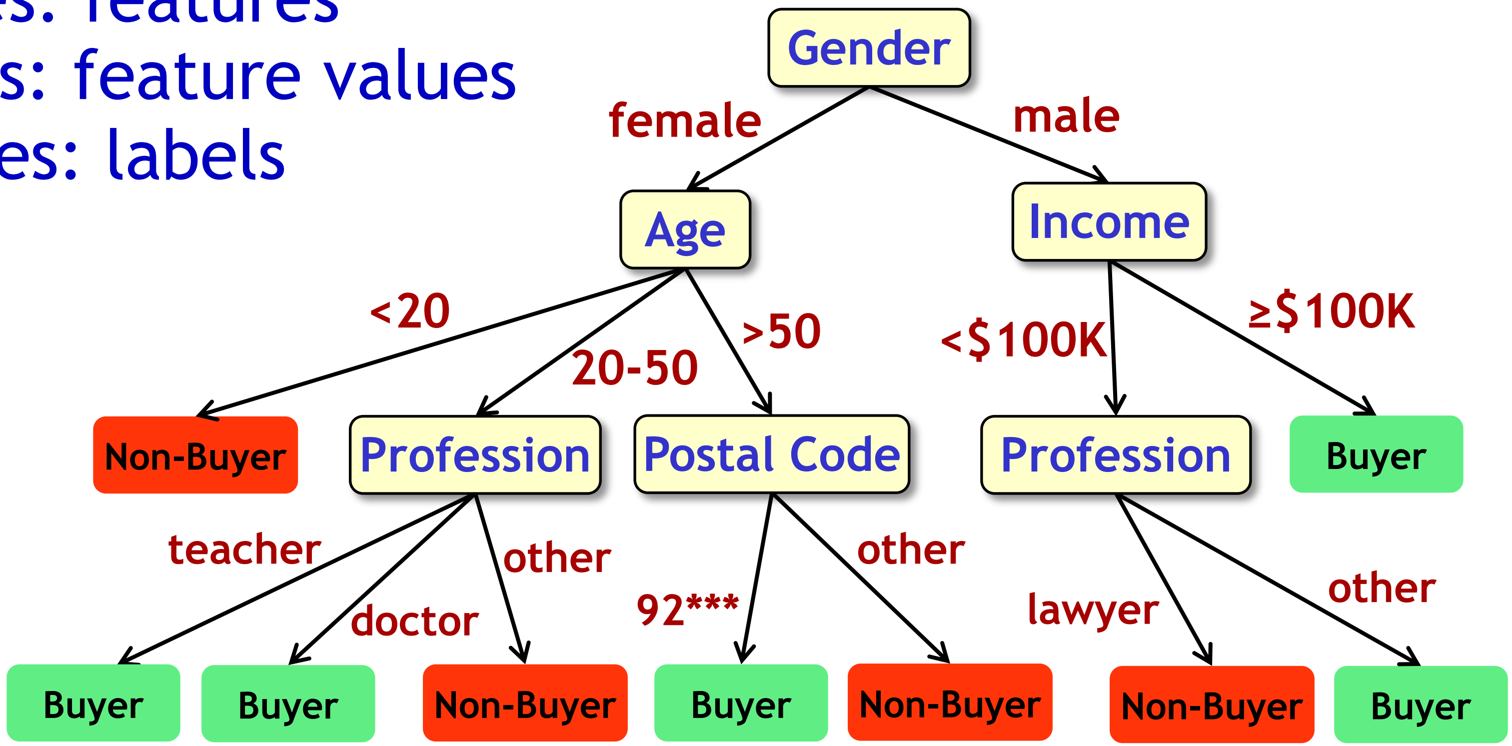
Can refine by weighting average by distance

Decision Trees

- Use the training data to construct a decision tree
- Use the decision tree to classify new data

Decision Trees

Nodes: features
Edges: feature values
Leaves: labels



New data item to classify:
Navigate tree based on feature values

Decision Trees

Primary challenge is building good decision trees from training data

- Which features and feature values to use at each choice point
- HUGE number of possible trees even with small number of features and values

Common approach: “forest” of many trees, combine the results

- Still impossible to consider all trees

Naïve Bayes

Given new data item *i*, based on *i*'s feature values and the training data, compute the probability of each possible label. Pick highest one.

Efficiency relies on conditional independence assumption:

Given any two features F_1,F_2 and a label L, the probability that $F_1=v_1$ for an item with label L is independent of the probability that $F_2=v_2$ for that item

Examples:

gender and age? income and postal code?

Naïve Bayes

Given new data item *i*, based on *i*'s feature values and the training data, compute the probability of each possible label. Pick highest one.

Efficiency relies on conditional independence assumption:

…bel L, the …h label L is … $F_2=v_2$ for that item.

Conditional independence assumption often doesn't hold, which is why the approach is "naive"

Examples:

gender and age? income and…

Nevertheless the approach works very well in practice

Naïve Bayes Example

Predict temperature category for a country based on whether the country has coastline and whether it is in the EU

country	coastline	EU	tempAvg	category
Albania	yes	no	15.18	hot
Andorra	no	no	9.60	warm
Belarus	no	no	5.95	cool
Belgium	yes	yes	9.65	warm
Bosnia and Herzegov	no	no	9.60	warm
Bulgaria	yes	yes	10.44	warm
Croatia	yes	yes	10.87	warm
Czech Republic	no	yes	7.86	cool
Denmark	yes	yes	7.63	cool
Estonia	yes	yes	4.59	cold
Finland	yes	yes	3.49	cold
Germany	yes	yes	7.87	cool
Greece	yes	yes	16.90	hot
Hungary	no	yes	9.60	warm
Ireland	yes	yes	9.30	warm

Naïve Bayes Preparation

Step 1: Compute fraction (probability) of items in each category

cold	.18
cool	.38
warm	.24
hot	.20

Naïve Bayes Preparation

Step 2: For each category, compute fraction of items in that category for each feature and value

cold (.18)	coastline=yes	.83
	coastline=no	.17
	EU=yes	.67
	EU=no	.33
cool (.38)	coastline=yes	.69
	coastline=no	.31
	EU=yes	.77
	EU=no	.23

warm (.24)	coastline=yes	.5
	coastline=no	.5
	EU=yes	.5
	EU=no	.5
hot (.20)	coastline=yes	1.0
	coastline=no	.0
	EU=yes	.71
	EU=no	.29

Naïve Bayes Prediction

New item: France, coastline=yes, EU=yes

For each category: probability of category times product of probabilities of new item's features in that category. Pick highest.

category	prob.	coastline=yes	EU=yes	product
cold	.18	.83	.67	.10
cool	.38	.69	.77	.20
warm	.24	.5	.5	.06
hot	.20	1.0	.71	.14

Naïve Bayes Prediction

New item: France, coastline=yes, EU=yes

For each category: probability of category times product of probabilities of new item's features in that category. Pick highest.

category	prob.	coastline=yes	EU=yes	product
cold	.18	.83	.67	.10
cool	.38	.69	.77	.20
warm	.24	.5	.5	.06
hot	.20	1.0	.71	.14

Naïve Bayes Prediction

New item: Serbia, coastline=no, EU=no

For each category: probability of category times product of probabilities of new item's features in that category. Pick highest.

category	prob.	coastline=no	EU=no	product
cold	.18	.17	.33	.01
cool	.38	.31	.23	.03
warm	.24	.5	.5	.06
hot	.20	.0	.29	.00

Naïve Bayes Prediction

New item: Serbia, coastline=no, EU=no

For each category: probability of category times product of probabilities of new item's features in that category. Pick highest.

category	prob.	coastline=no	EU=no	product
cold	.18	.17	.33	.01
cool	.38	.31	.23	.03
warm	.24	.5	.5	.06
hot	.20	.0	.29	.00

Naïve Bayes Prediction

New item: Austria, coastline=no, EU=yes

For each category: probability of category times product of probabilities of new item's features in that category. Pick highest.

category	prob.	coastline=no	EU=yes	product
cold	.18	.17	.67	.02
cool	.38	.31	.77	.09
warm	.24	.5	.5	.06
hot	.20	.0	.71	.0

Naïve Bayes Prediction

New item: Austria, coastline=no, EU=yes

For each category: probability of category times product of probabilities of new item's features in that category. Pick highest.

category	prob.	coastline=no	EU=yes	product
cold	.18	.17	.67	.02
cool	.38	.31	.77	.09
warm	.24	.5	.5	.06
hot	.20	.0	.71	.0

Naïve Bayes Prediction

New item: Austria, coastline=no, EU=yes

For e… times
prod… tures
in th…

Many presentations of Naïve Bayes include an additional normalization step so the final products are probabilities that sum to 1.0. The choice of label is unchanged, so we've omitted that step for simplicity.

ca…				…uct
				…2
cool	.38	.31	.77	.09
warm	.24	.5	.5	.06
hot	.20	.0	.71	.0

Your Turn: World Cup Data

Predict whether team ends in group or knockout stage based on number of yellow cards per game and number of red cards per game

team	games	stage	yellowCards	redCards	yellowPerGame	yellows	redPerGame	reds
Algeria	3	group	4	2	1.33	low	0.67	high
Argentina	5	knockout	7	0	1.40	low	0.00	none
Australia	3	group	7	2	2.33	high	0.67	high
Brazil	5	knockout	7	2	1.40	low	0.40	high
Cameroon	3	group	5	0	1.67	medium	0.00	none
Chile	4	knockout	13	1	3.25	high	0.25	medium
Denmark	3	group	6	0	2.00	medium	0.00	none
England	4	knockout	6	0	1.50	medium	0.00	none
Germany	6	knockout	8	1	1.33	low	0.17	medium
Ghana	5	knockout	11	0	2.20	high	0.00	none
Greece	3	group	5	0	1.67	medium	0.00	none
Honduras	3	group	7	0	2.33	high	0.00	none
Italy	3	group	5	0	1.67	medium	0.00	none
Ivory Coast	3	group	5	0	1.67	medium	0.00	none
Japan	4	knockout	7	0	1.75	medium	0.00	none
Mexico	4	knockout	9	0	2.25	high	0.00	none
Netherlands	6	knockout	15	0	2.50	high	0.00	none

Your Turn

group (.5)	yellows=low	.20
	yellows=medium	.47
	yellows=high	.33
	reds=none	.60
	reds=medium	.27
	reds=high	.13

knockout (.5)	yellows=low	.33
	yellows=medium	.34
	yellows=high	.33
	reds=none	.67
	reds=medium	.27
	reds=high	.06

1. France: yellows=medium, reds=medium
   group or knockout?
2. USA: yellows=high, reds=none
   group or knockout?

Feature Management

Real applications often have thousands of features, too many for classification algorithms to handle well

Sometimes useful features are hidden or missing

Feature Management

Real applications often have thousands of features, too many for classification algorithms to handle well

- Feature selection – select subset of features that are independent and predictive
- Dimensionality reduction – combine multiple features into one value

  Replace [salary,bonus,options] with income

  Replace [passes,minutes] with passes-per-minute

Sometimes useful features are hidden or missing

Feature Management

Real applications often have thousands of features, too many for classification algorithms to handle well

Sometimes useful features are hidden or missing

- Feature engineering – add features from other data or domain knowledge

  distance-from-coast, elevation (for temperature)

  average player temperament (for yellow and red cards)

  product ratings from review site

Deep Neural Networks

Neural Networks

- Machine learning method modeled loosely after connected neurons in brain
- Invented decades ago but not successful
- Recent resurgence enabled by:
  - Powerful computing that allows for many layers (making the network “deep”)
  - Massive data for effective training

Deep Neural Networks

= Deep Learning

- Huge breakthrough in effectiveness and reach of machine learning
- Accurate predictions across many domains
- Big plus: Automatically identifies features in unstructured data
  (e.g., images, videos, text)

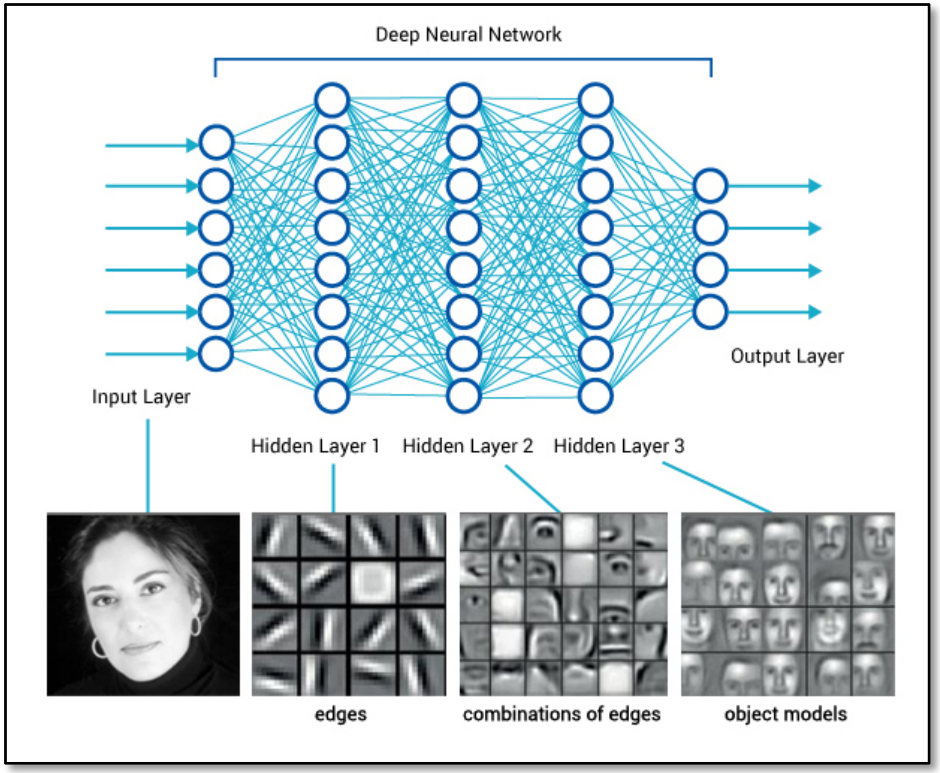
Deep Neural Networks

General idea

- Multiple layers, each layer transforms inputs to provide new features or structures for next layer
- Iterate on training data, checking accuracy and improving network

Reality

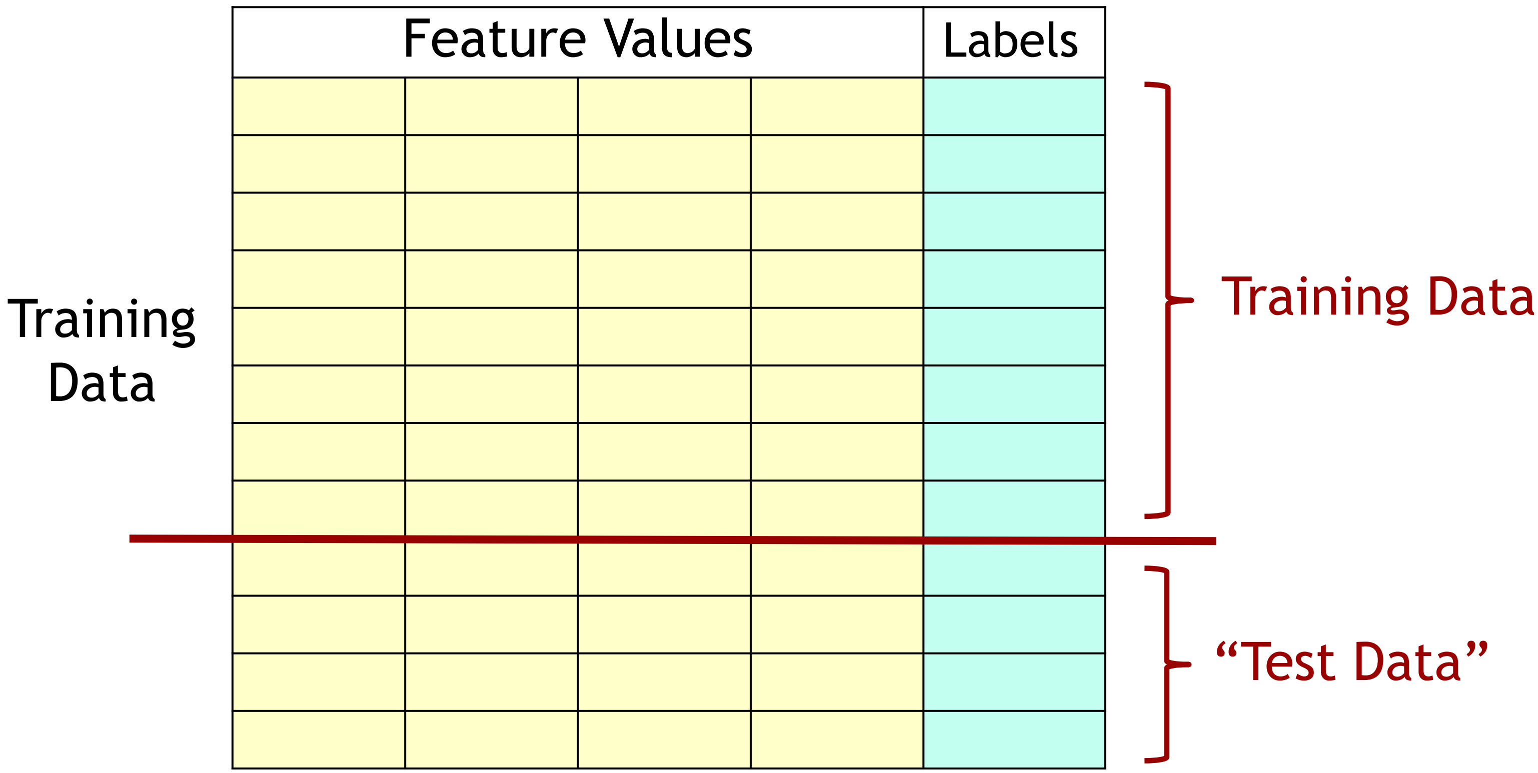
- Complex and mysterious, often used without full understanding
- Results not "explainable"



Training and Test

Created machine learning model from training data.
How do you know whether it's a good model?

- Try it on known data



Confusion Matrix

Full information about results on test data

Prediction

Actual	cold	cool	warm	hot
cold	12	5	2	0
cool	8	69	12	3
warm	2	16	57	5
hot	1	1	9	15

Accuracy
.718

- Basic accuracy = % correct = Σ(diagonal) / total
- When numbers or ordinal categories, can also incorporate distance

Other Methods You Might Come Across

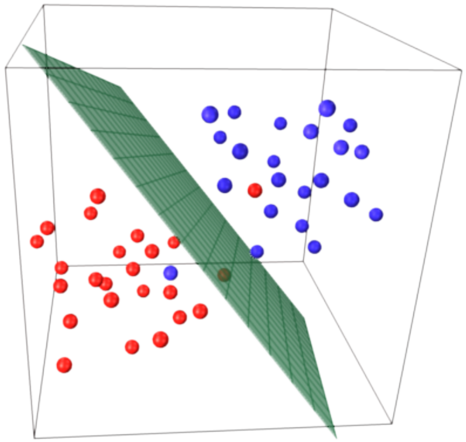
Logistic Regression

- Typically for two labels only ("binary classifier")
- Recall regression model is function f from predictor values to numeric output value
- Labels L_1 + L_2, from training data obtain function:

  f(*feature-values*) = *probability of item having label* L_1

Support Vector Machine

- Also for binary classification
- Features = multidimensional space
- From training data SVM finds hyper-plane that best divides space according to labels



Classification Summary

- Supervised machine learning
- Training data, each example:
  - Set of feature values – numeric or categorical
  - Categorical output value – label
- Model is "function" from feature values to label
  - Use model to predict label for new feature values

Classification Summary

- Approaches we covered
  - K-nearest neighbors
    relies on distance (or similarity) function
  - Decision trees
    relies on finding good trees/forests
  - Naïve Bayes
    relies on conditional independence assumption
  - Deep neural networks
    relies on large data sets and powerful computing