Data Mining with Weka

Class 4 – Lesson 1

Classification boundaries

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Lesson 4.1 Classification boundaries

Class 1
Getting started with Weka

Class 2
Evaluation

Class 3
Simple classifiers

Class 4
More classifiers

- Lesson 4.1 Classification boundaries
- Lesson 4.2 Linear regression
- ~~Lesson 4.3 Classification by regression~~
- Lesson 4.4 Logistic regression
- ~~Lesson 4.5 Support vector machines~~
- Lesson 4.6 Ensemble learning

Class 5
Putting it all together

Lesson 4.1 Classification boundaries

Weka's Boundary Visualizer for OneR

- Open **iris.2D.arff**, a 2D dataset
  - *(could create it yourself by removing sepallength and sepalwidth attributes)*
- Weka GUI Chooser: **Visualization>BoundaryVisualizer**
  - *open iris.2D.arff*
  - *Note: petallength on X, petalwidth on Y*
  - *choose rules>OneR*
  - *check Plot training data*
  - *click Start*
  - *in the Explorer, examine OneR's rule*

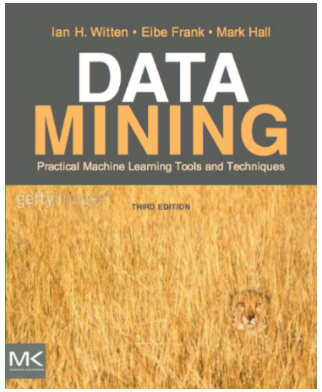
Lesson 4.1 Classification boundaries

Visualize boundaries for other schemes

- Choose **lazy>IBk**
  - *Plot training data; click Start*
  - *k = 5, 20; note mixed colors*
- Choose **bayes>NaiveBayes**
  - *set useSupervisedDiscretization to true*
- Choose **trees>J48**
  - *relate the plot to the Explorer output*
  - *experiment with minNumbObj = 5 and 10: controls leaf size*

Lesson 4.1 Classification boundaries

- Classifiers create boundaries in instance space
- Different classifiers have different biases
- Looked at OneR, IBk, NaiveBayes, J48
- Visualization restricted to numeric attributes, and 2D plots



Course text

- Section 17.3 *Classification boundaries*

Data Mining with Weka

Class 4 – Lesson 2

Linear regression

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Lesson 4.2: Linear regression

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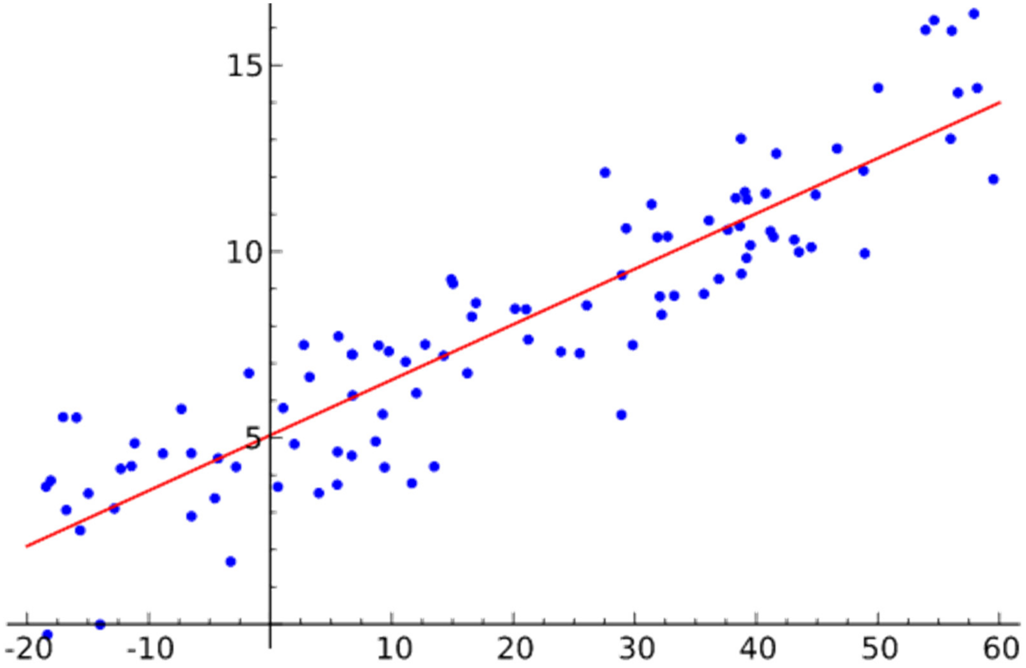
- Class 5 **Putting it all together**

Lesson 4.2: Linear regression

Numeric prediction (called "regression")

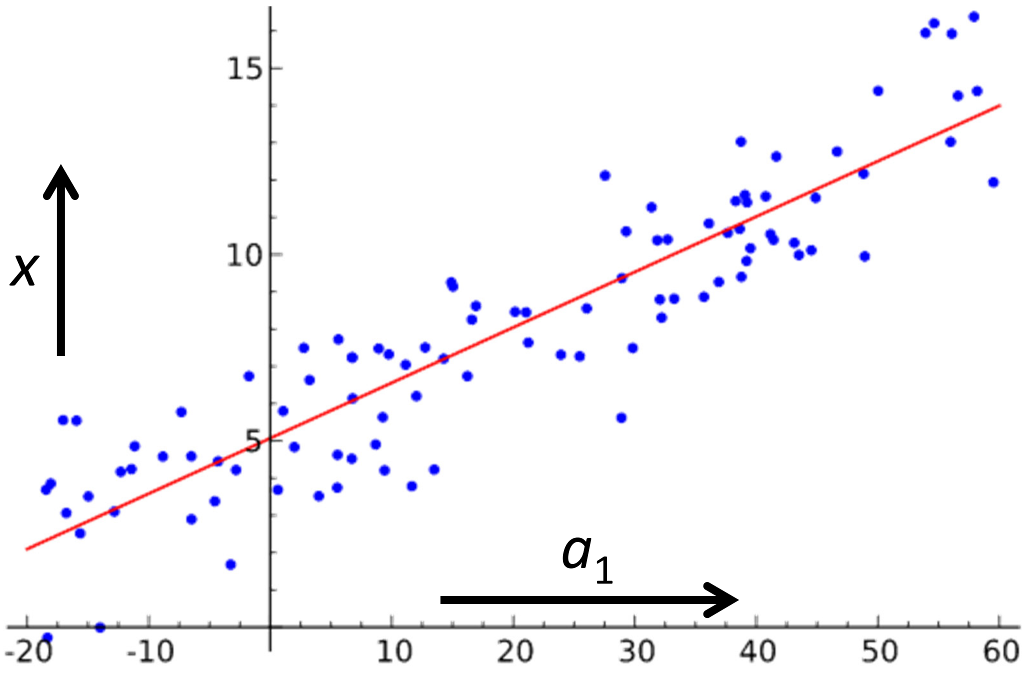
- Data sets so far: nominal and numeric attributes, but only nominal classes
- Now: numeric classes
- Classical statistical method (from 1805!)



Lesson 4.2: Linear regression

$$x = w_0 + w_1 a_1 + w_2 a_2 + \ldots + w_k a_k$$

(Works most naturally
with numeric attributes)



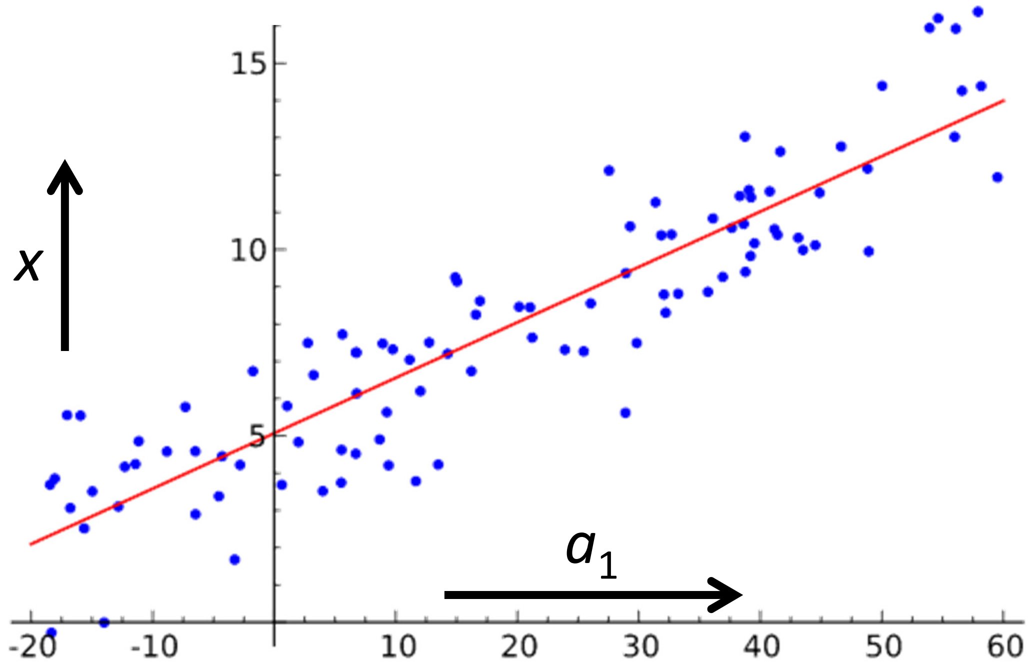
Lesson 4.2: Linear regression

$$x = w_0 + w_1 a_1 + w_2 a_2 + \ldots + w_k a_k$$

❖ Calculate weights from training data

❖ Predicted value for first training instance $a^{(1)}$

$$w_0 a_0^{(1)} + w_1 a_1^{(1)} + w_2 a_2^{(1)} + \ldots + w_k a_k^{(1)} = \sum_{j=0}^{k} w_j a_j^{(1)}$$



Lesson 4.2: Linear regression

$$x = w_0 + w_1 a_1 + w_2 a_2 + \ldots + w_k a_k$$

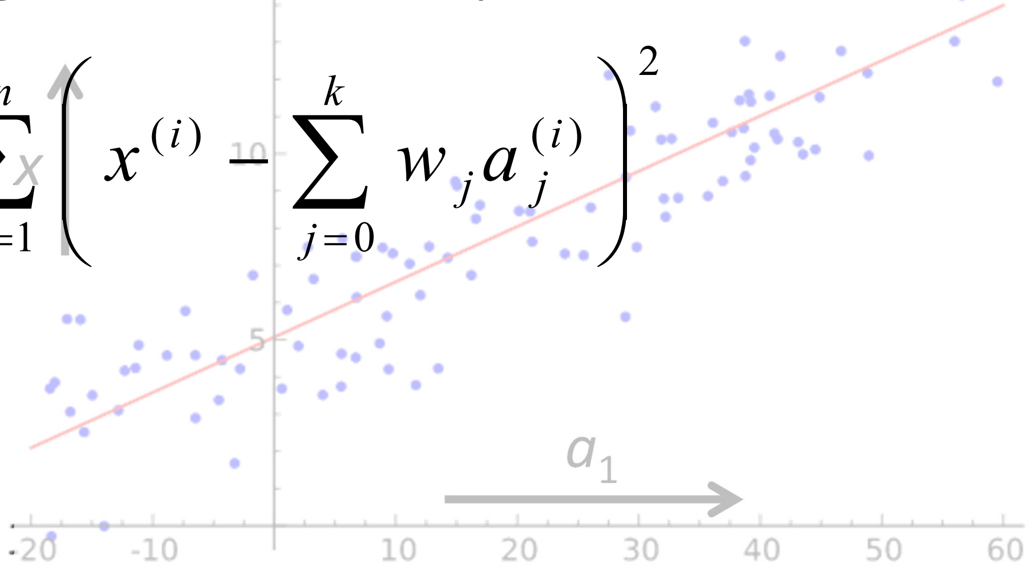
❖ Calculate weights from training data

❖ Predicted value for first training instance $a^{(1)}$

$$w_0 a_0^{(1)} + w_1 a_1^{(1)} + w_2 a_2^{(1)} + \ldots + w_k a_k^{(1)} = \sum_{j=0}^{k} w_j a_j^{(1)}$$

❖ Choose weights to minimize squared error on training data

$$\sum_{i=1}^{n} \left(x^{(i)} - \sum_{j=0}^{k} w_j a_j^{(i)} \right)^2$$



Lesson 4.2: Linear regression

- Standard matrix problem
  - *Works if there are more instances than attributes*
    roughly speaking

- Nominal attributes
  - *two-valued: just convert to 0 and 1*
  - *multi-valued … will see in end-of-lesson Activity*

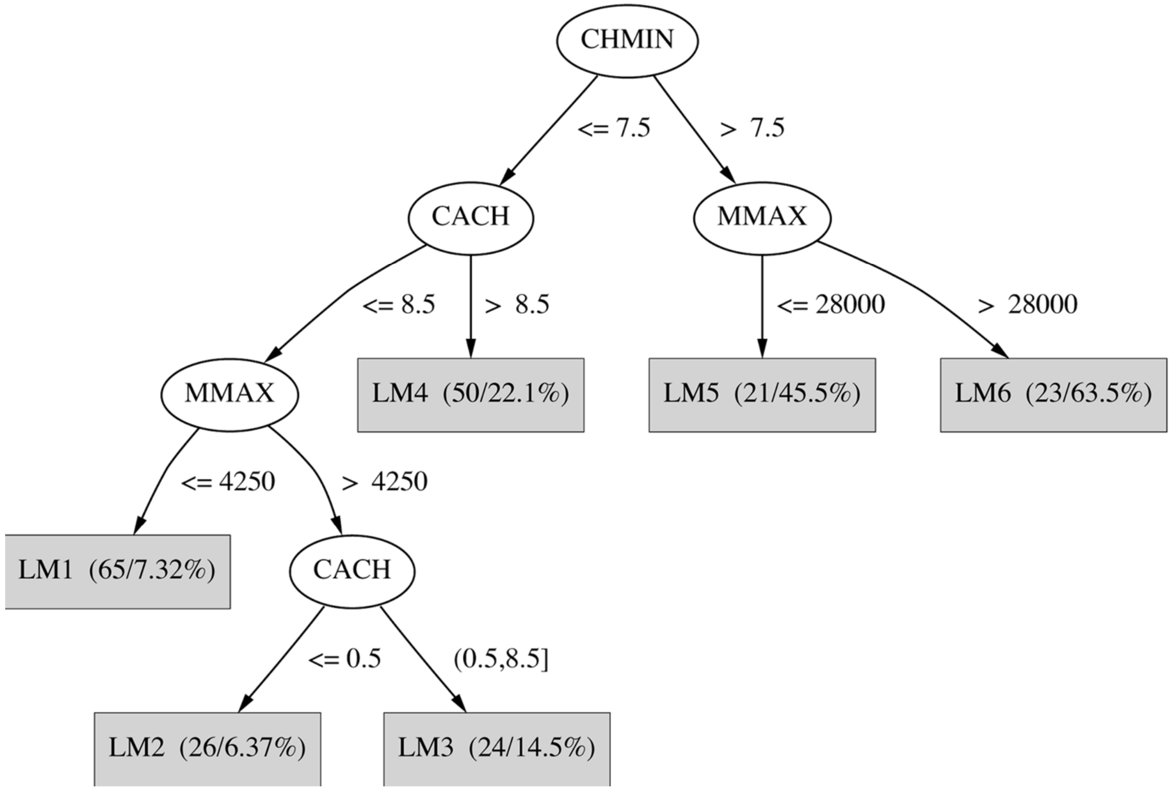
Lesson 4.2: Linear regression

- Open file cpu.arff: all numeric attributes and classes
- Choose functions>LinearRegression
- Run it
- Output:
  - *Correlation coefficient*
  - *Mean absolute error* $$\frac{|p_1 - a_1| + \ldots + |p_n - a_n|}{n}$$
  - *Root mean squared error* $$\sqrt{\frac{(p_1 - a_1)^2 + \ldots + (p_n - a_n)^2}{n}}$$
  - *Relative absolute error* $$\frac{|p_1 - a_1| + \ldots + |p_n - a_n|}{|a_1 - \bar{a}| + \ldots + |a_n - \bar{a}|}$$
  - *Root relative squared error* $$\sqrt{\frac{(p_1 - a_1)^2 + \ldots + (p_n - a_n)^2}{(a_1 - \bar{a})^2 + \ldots + (a_n - \bar{a})^2}}$$
- Examine model

Lesson 4.2: NON Linear regression

Model tree

- Each leaf has a linear regression model
- Linear patches approximate continuous function



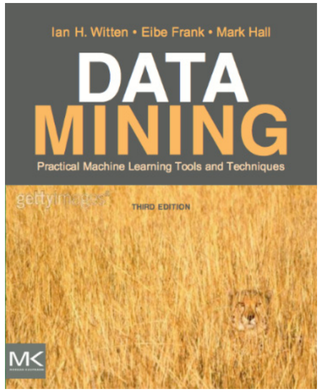
Lesson 4.2: NON Linear regression

- Choose **trees>M5P**
- Run it
- Output:
  - *Examine the linear models*
  - *Visualize the tree*

- Compare performance with the **LinearRegression** result: you do it!

Lesson 4.2: Linear regression

- Well-founded, venerable mathematical technique: **functions>LinearRegression**
- Practical problems often require non-linear solutions
- **trees>M5P** builds trees of regression models



Course text

- Section 4.6 *Numeric prediction: Linear regression*

Data Mining with Weka

Class 4 – Lesson 3

Classification by regression

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Data Mining with Weka

Class 4 – Lesson 4

Logistic regression

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Lesson 4.4: Logistic regression

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Class 5
Putting it all together

Lesson 4.4: Logistic regression

Can do better by using prediction probabilities

Probabilities are often useful anyway …

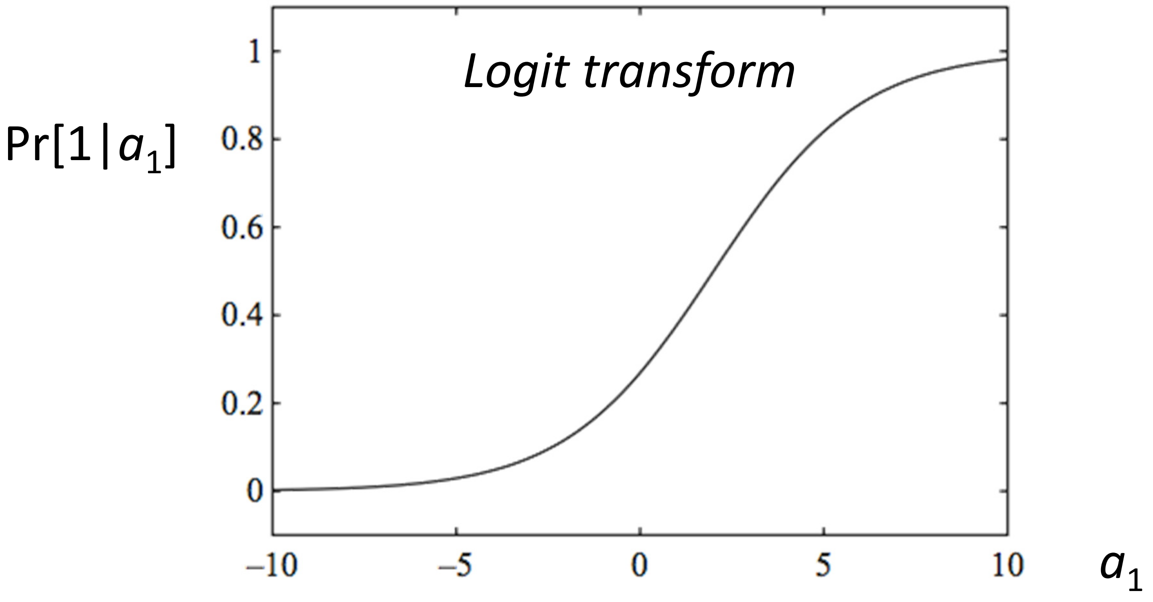
- Naïve Bayes produces them (obviously)
  - *Open **diabetes.arff** and run **Bayes>NaiveBayes*** **with 90% percentage split**
  - *Look at columns: actual, predicted, error, prob distribution*
- Other methods produce them too …
  - *Run **rules>ZeroR**. Why probabilities* [*0.648, 0.352*] for [*tested_negative, tested_positive*]?
  - *90% training fold has 448 negatve, 243 positive instances*
  - *(448+1)/(448+1 + 243+1) = 0.648* [*cf. Laplace correction, Lesson 3.2*]
  - *Run **trees>J48***
  - *J48 uses probabilities internally to help with pruning*

Make linear regression produce probabilities too!

Lesson 4.4: Logistic regression

- Linear regression: calculate a linear function and then a threshold
- Logistic regression: estimate class probabilities directly

$$\Pr[1 \mid a_1, a_2, \ldots, a_k] = 1/(1+\exp(-w_0 - w_1 a_1 - \ldots - w_k a_k))$$



- Choose weights to maximize the log-likelihood (not minimize the squared error):

$$\sum_{i=1}^{n} (1-x^{(i)}) \log(1-\Pr[1 \mid a_1^{(1)}, a_2^{(2)}, \ldots, a_k^{(k)}]) + x^{(i)} \log(\Pr[1 \mid a_1^{(1)}, a_2^{(2)}, \ldots, a_k^{(k)}])$$

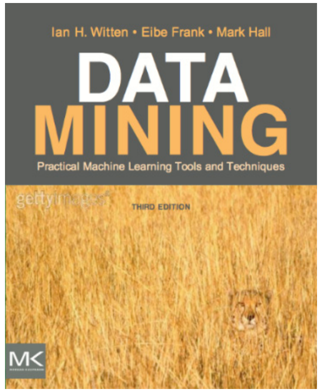
Lesson 4.4: Logistic regression

❖ Open file **diabetes.arff**			
❖ Classification-by-regression		76.8%	mean of 10 runs
❖ cf	ZeroR	65.1%	65.1%
	Naïve Bayes	76.3%	75.8%
	J48	73.8%	74.5%
❖ **Apply functions>Logistic**		77.2%	77.5%

- Extension to multiple classes …
  - Perform a regression for each class?
    (like multi-response regression)
  - No. Probabilities won't sum to 1
  - Can be tackled as a joint optimization problem

Lesson 4.4: Logistic regression

- Logistic regression is popular and powerful
- Uses logit transform to predict probabilities directly
  - like Naïve Bayes
- Also learned about
  - Prediction probabilities from other methods
  - How to calculate probabilities from ZeroR



Course text

- Section 4.6 *Numeric prediction: Logistic regression*

Data Mining with Weka

Class 4 – Lesson 6

Ensemble learning

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Lesson 4.6: Ensemble learning

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Lesson 4.4 Logistic regression

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Lesson 4.6 Ensemble learning

Lesson 4.6: Ensemble learning

Committee structure: build different “experts,” let them vote

- Often improves predictive performance
- Produces output that is hard to analyze
  - *but: there are approaches that aim to produce a single comprehensible structure*
- Methods
  - *Bagging*
  - *Randomization*
  - *Boosting*
  - *Stacking*

Lesson 4.6: Ensemble learning

Bagging

- Several training sets of the same size
  - *produce them by sampling … with replacement*
- Build model for each one
  - *use same machine learning scheme*
- Combine predictions by voting

  (or, for regression, averaging)
- Very suitable for “unstable” learning schemes
  - *small change in training data can make big change in model*
  - *example: decision trees … but not Naïve Bayes or instance-based learning*
- Weka: meta>Bagging
- E.g. with glass.arff
  - *J48* *66.8%*
  - *Bagging (default parameters)* *72.4%*

Lesson 4.6: Ensemble learning

Randomization: random forests

- Randomize the algorithm, not the training data
  - *how you randomize depends on the algorithm*
- Random forests
  - *attribute selection for J48 decision tree: don’t pick the best, pick randomly from the k best options*
  - *generally improves decision trees*
- Weka: trees>RandomForests
  - *options: number of trees (default 10); maximum depth of trees; number of attributes*
- E.g. with glass.arff
  - *J48* 66.8%
  - *RandomForests (default parameters)* 75.2%

Lesson 4.6: Ensemble learning

Boosting

- Iterative: new models are influenced by performance of previously built ones
  - *extra weight for instances that are misclassified ("hard" ones)*
  - *encourage new model to become an "expert" for instances misclassified by earlier models*
  - *Intuitive justification: committee members should complement each other's expertise*
- Uses voting (or, for regression, averaging)
  - *but weights models according to their performance*
- Often dramatically improves performance
- Weka: meta>AdaBoostM1
- E.g. with glass.arff
  - *J48* *66.8%*
  - *AdaBoostM1 (using J48)* *74.3%*

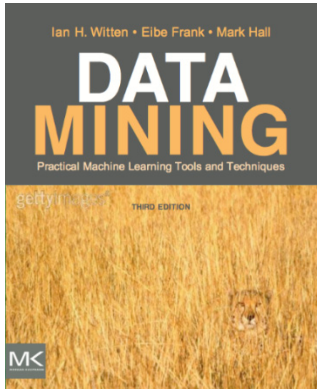
Lesson 4.6: Ensemble learning

Stacking

- Combine predictions of base learners using a *meta learner* (not voting)
  - *base learners: level-0 models*
  - *meta learner: level-1 model*
  - *predictions of base learners are input to meta learner*
- Base learners are usually different schemes
- Can't use predictions on training data to generate data for level-1 model!
  - *Instead use cross-validation-like scheme*
- Weka: meta>Stacking
  - *and StackingC, more efficient version*
  - *allow multiple level-0 models (by specifying a metaclassifier)*
- Quite hard to make stacking work well, but with glass.arff I got
  - *J48* *66.8%*
  - *StackingC, with default metaclassifier and base classifiers IBk, PART, J48* *72.5%*

Lesson 4.6: Ensemble learning

- Combining multiple models into "ensembles"
  - analogy with committees of humans
- Diversity helps, especially with "unstable" learners
  - when small changes in the training data can produce large changes in the learned model
- Create diversity by
  - Bagging: resampling the training set — meta>Bagging
  - Random forests: alternative branches in decision trees — trees>RandomForests
  - Boosting: focus on where the existing model makes errors — meta>AdaBoostM1
  - Stacking: combine results using another learner (instead of voting) — meta>Stacking



Course text

- Chapter 8 *Ensemble learning*

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