

Data Mining with Weka

Class 4 – Lesson 1

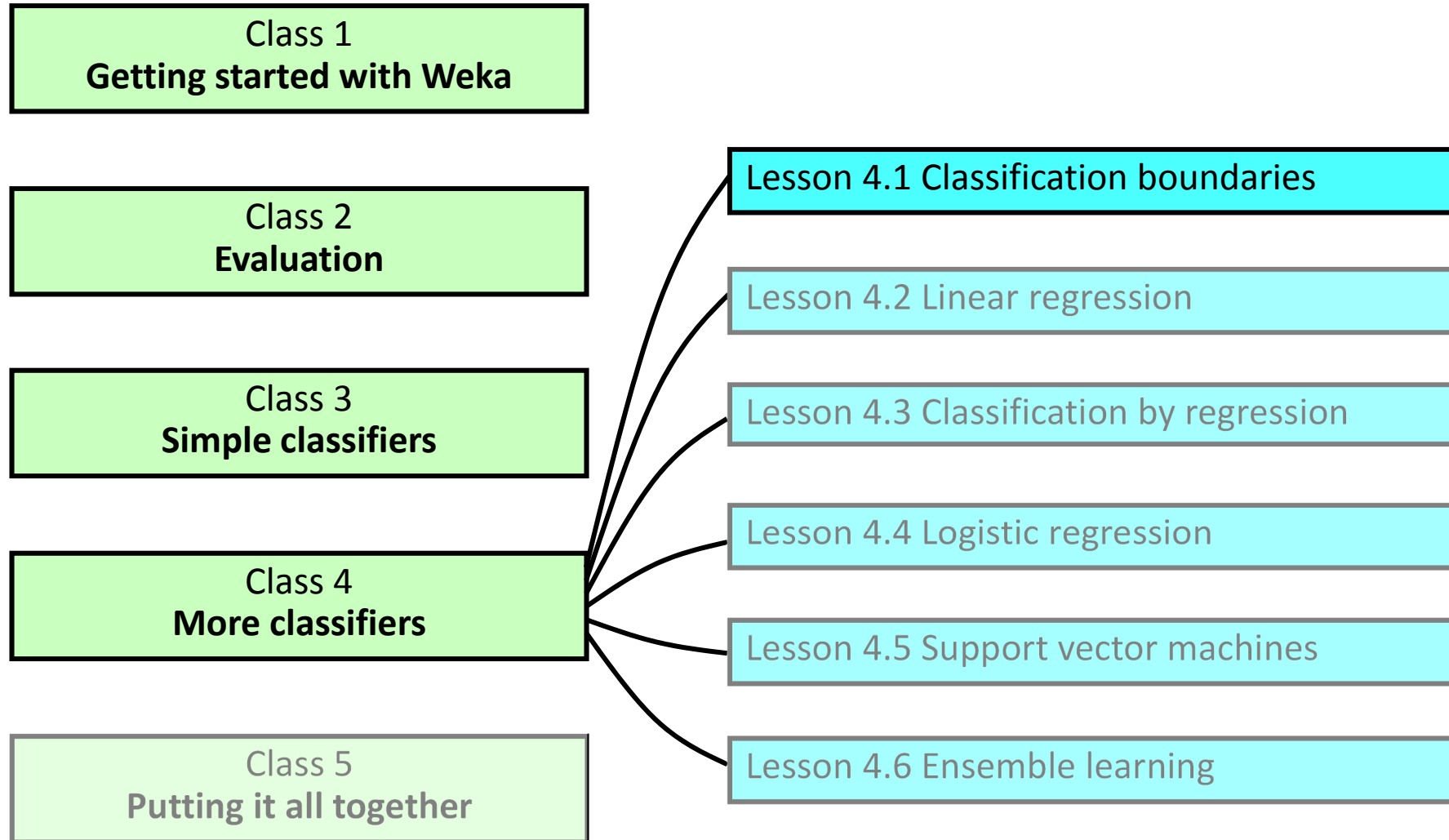
Classification boundaries

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Lesson 4.1 Classification boundaries



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

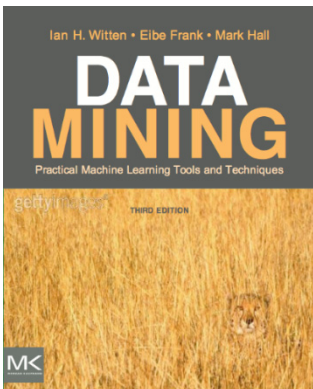
- ❖ Choose **lazy>IBk**
 - *Plot training data; click Start*
 - *$k = 5, 20$; note mixed colors*
- ❖ Choose **bayes>NaiveBayes**
 - *set `useSupervisedDiscretization` to `true`*
- ❖ Choose **trees>J48**
 - *relate the plot to the Explorer output*
 - *experiment with `minNumbObj` = 5 and 10: controls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

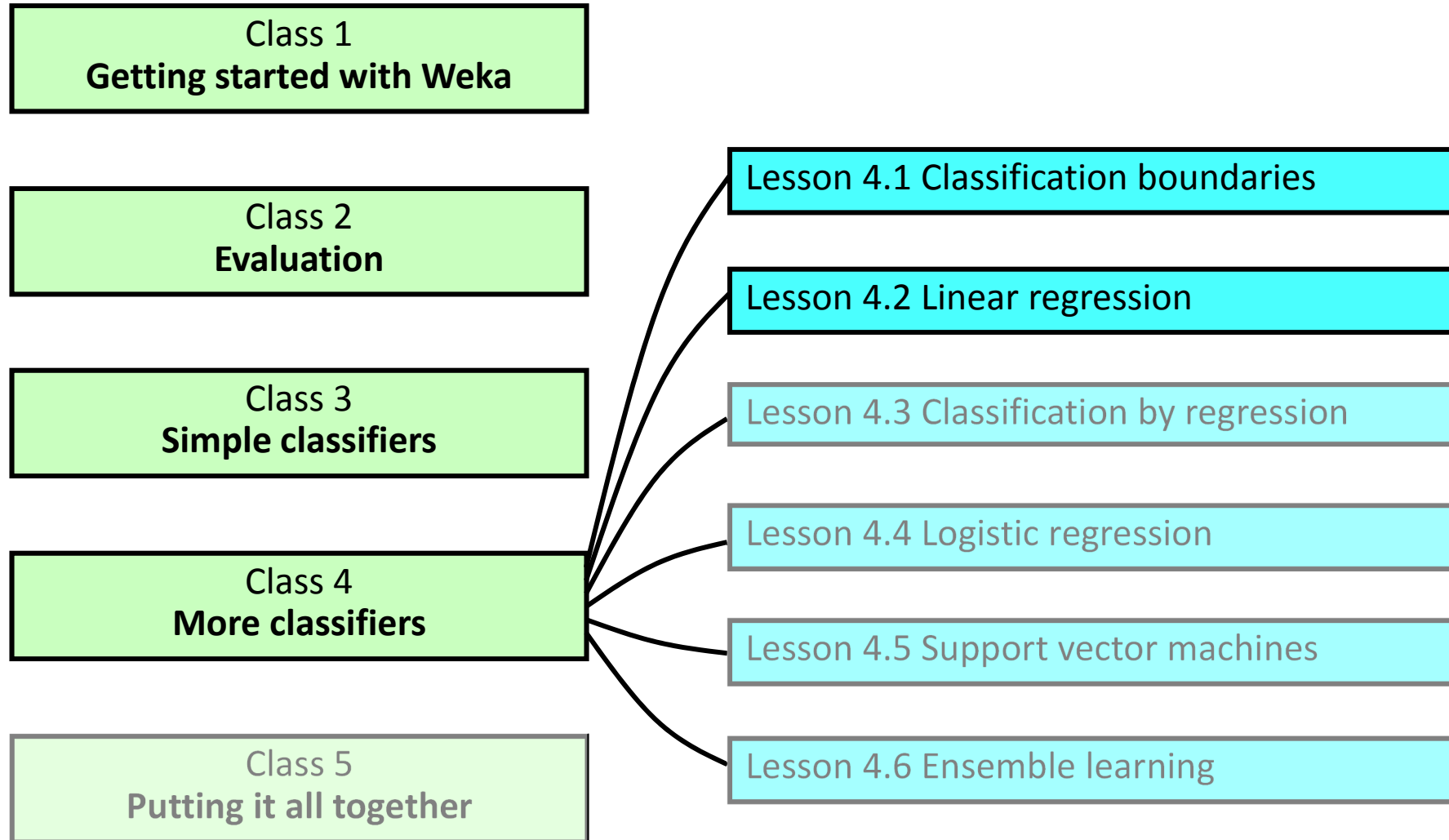
Linear regression

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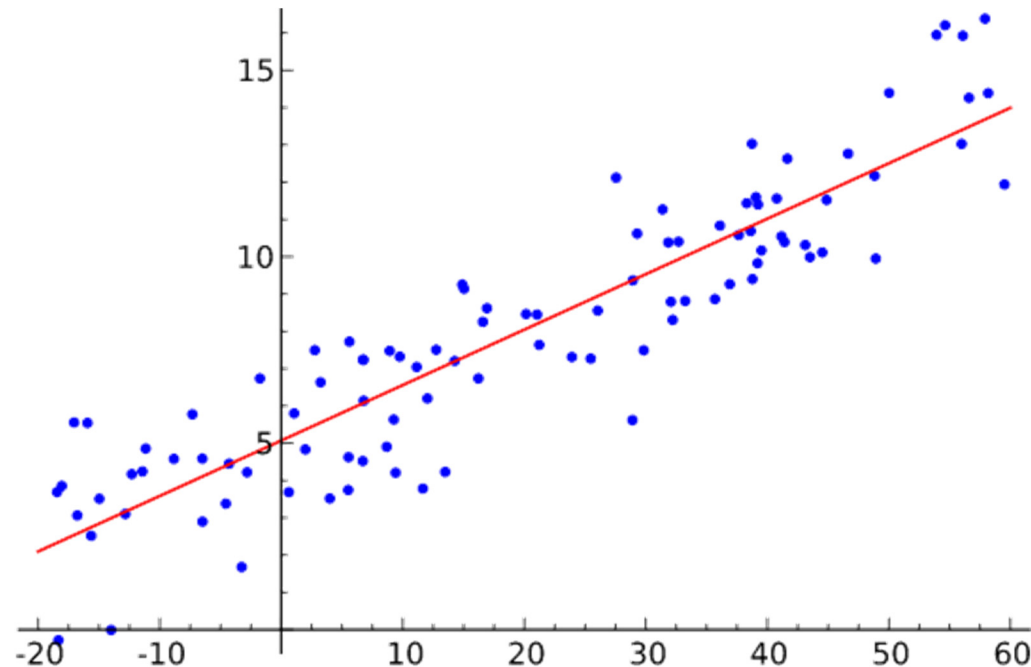
Lesson 4.2: Linear regression



Lesson 4.2: Linear regression

Numeric prediction (called “regression”)

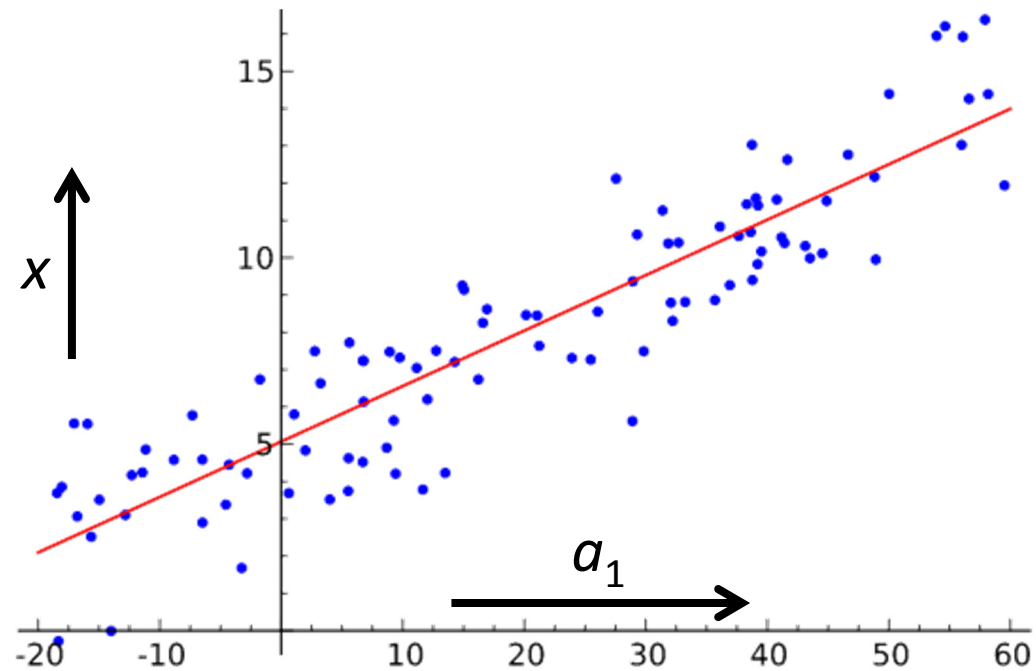
- ❖ Data sets so far: nominal and numeric attributes, but only nominal classes
- ❖ Now: numeric classes
- ❖ Classical statistical method (from 1805!)



Lesson 4.2: Linear regression

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

(Works most naturally
with numeric attributes)

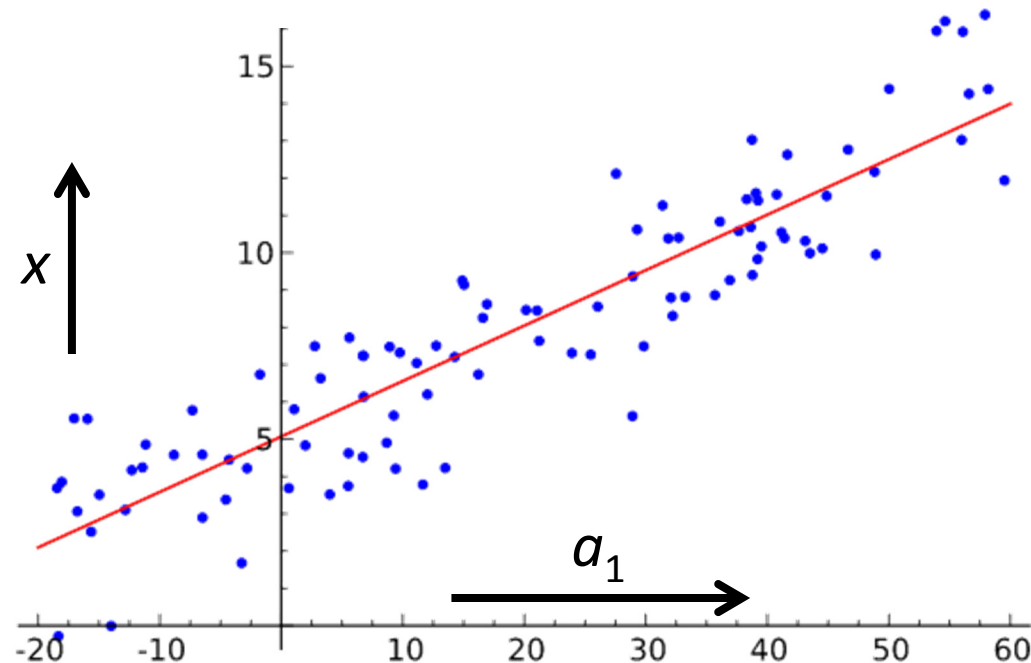


Lesson 4.2: Linear regression

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

- ❖ Calculate weights from training data
- ❖ Predicted value for first training instance $a^{(1)}$

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



Lesson 4.2: Linear regression

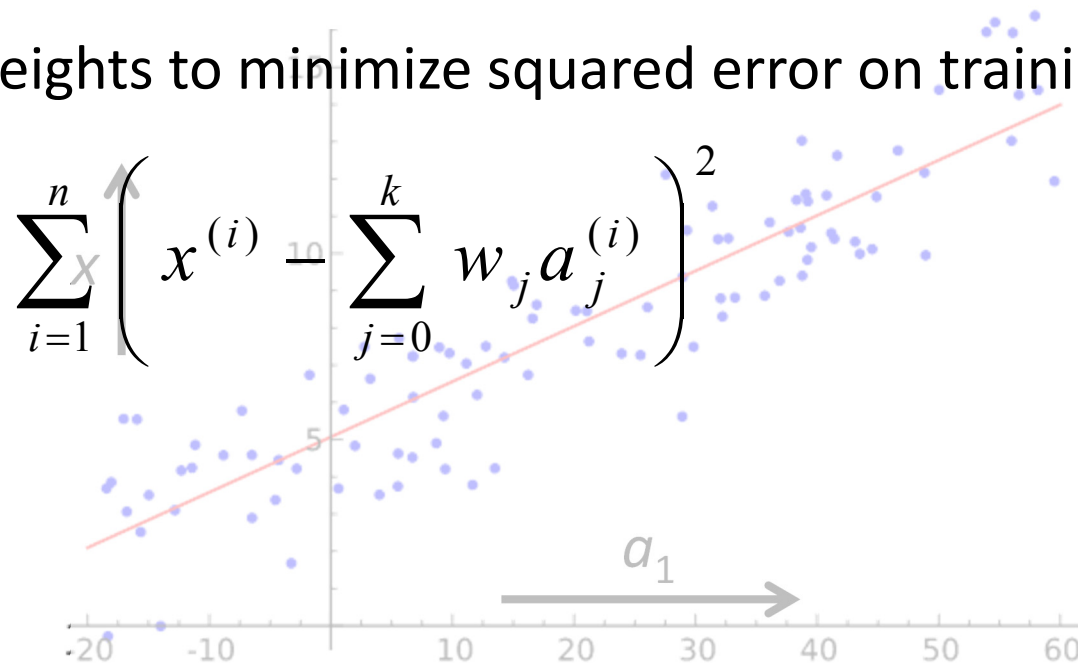
$$x = w_0 + w_1 a_1 + w_2 a_2 + \dots + w_k a_k$$

❖ Calculate weights from training data

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

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

❖ Choose weights to minimize squared error on training data



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

– Root mean squared error

– Relative absolute error

– Root relative squared error

❖ Examine model

$$\frac{|p_1 - a_1| + \dots + |p_n - a_n|}{n}$$

$$\sqrt{\frac{(p_1 - a_1)^2 + \dots + (p_n - a_n)^2}{n}}$$

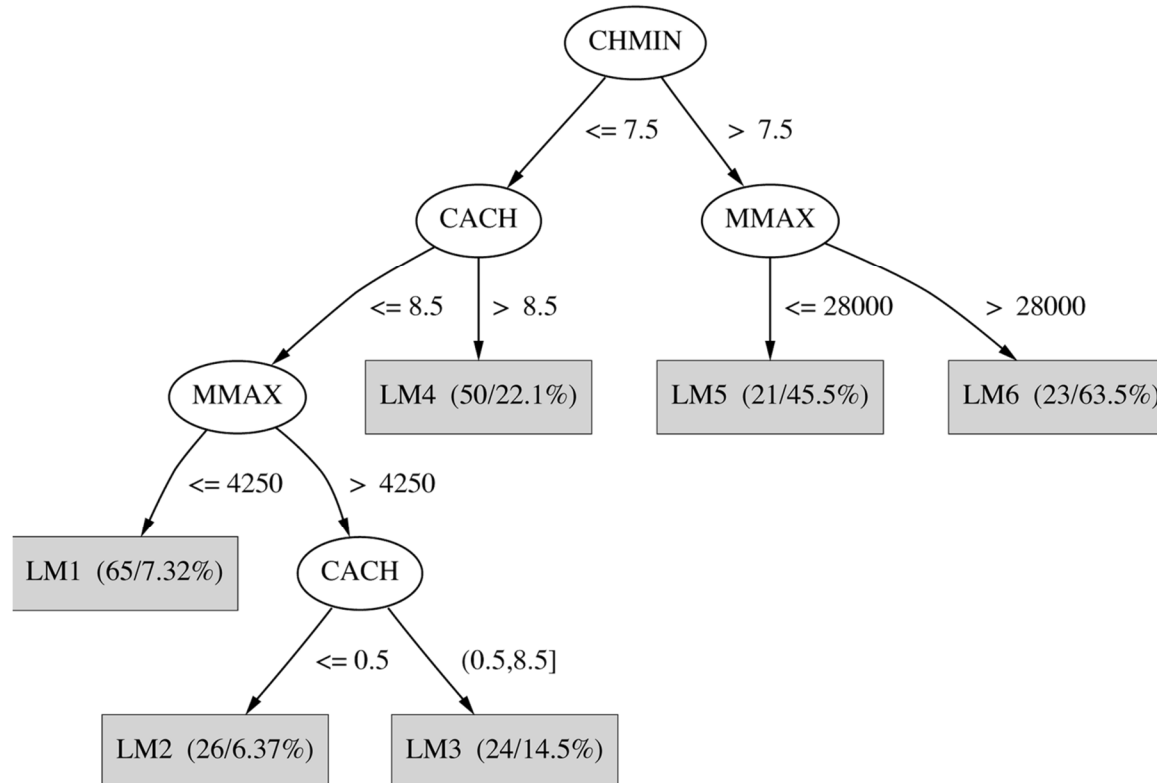
$$\frac{|p_1 - a_1| + \dots + |p_n - a_n|}{|a_1 - \bar{a}| + \dots + |a_n - \bar{a}|}$$

$$\sqrt{\frac{(p_1 - a_1)^2 + \dots + (p_n - a_n)^2}{(a_1 - \bar{a})^2 + \dots + (a_n - \bar{a})^2}}$$

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*

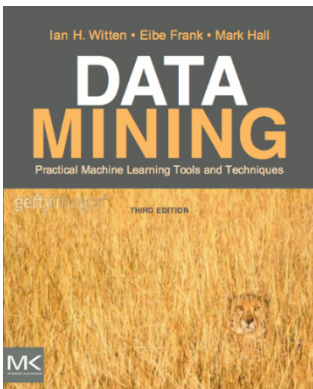
- ❖ Compare performance with the **LinearRegression** result: you do it!

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

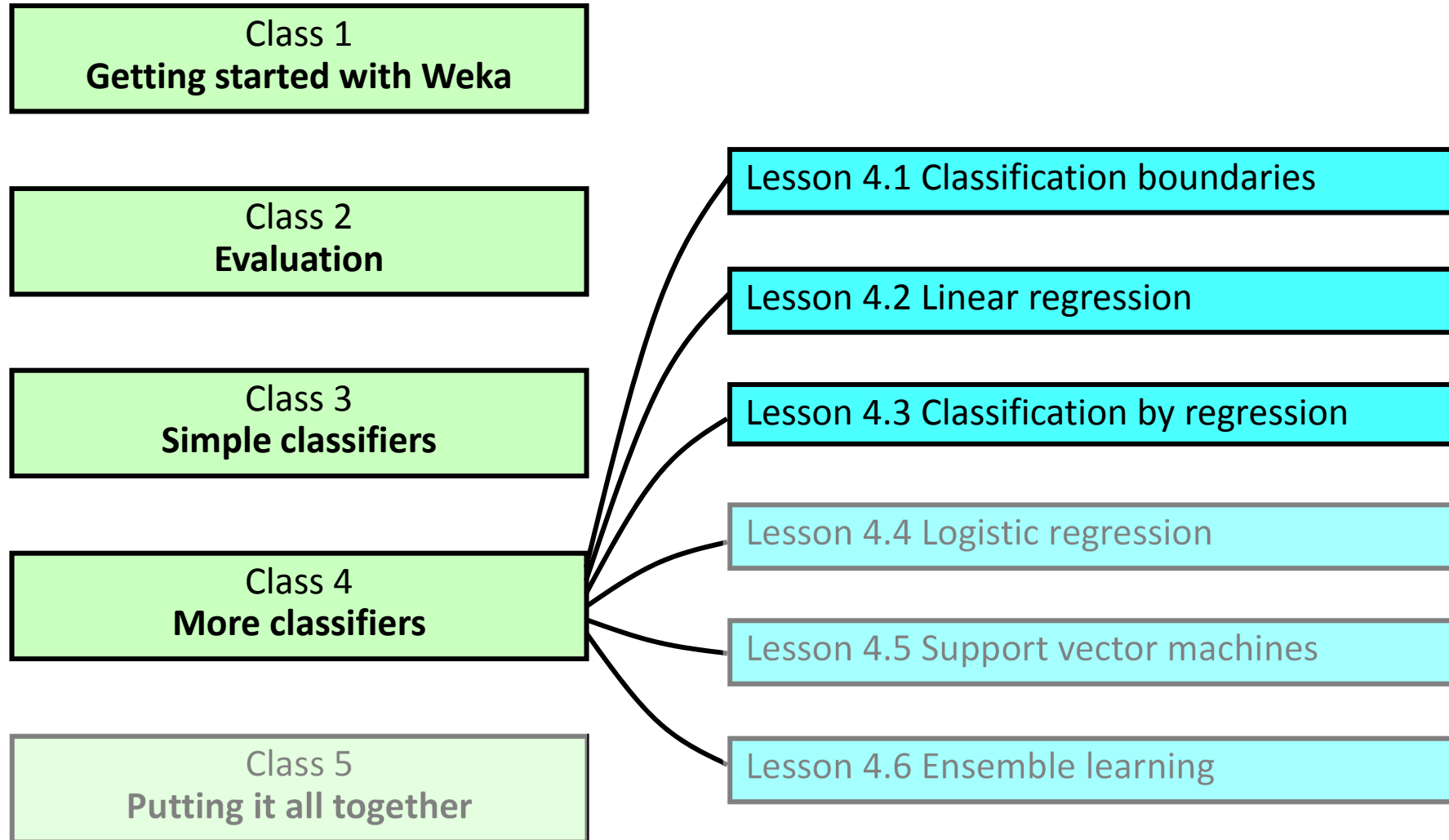
Classification by regression

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Lesson 4.3: Classification by regression



Lesson 4.3: Classification by regression

Can a regression scheme be used for classification? Yes!

Two-class problem

- ❖ Training: call the classes 0 and 1
- ❖ Prediction: set a threshold for predicting class 0 or 1

Multi-class problem: “multi-response linear regression”

- ❖ Training: perform a regression for each class
 - *Set output to 1 for training instances that belong to the class, 0 for instances that don't*
 - ❖ Prediction: choose the class with the largest output
- ... or use “pairwise linear regression”, which performs a regression for every pair of classes

Lesson 4.3: Classification by regression

Investigate two-class classification by regression

- ❖ Open file **diabetes.arff**
- ❖ Use the **NominalToBinary** attribute filter to convert to numeric
 - *but first set **Class: class (Nom)** to **No class**,
because attribute filters do not operate on the class value*
- ❖ Choose **functions>LinearRegression**
- ❖ Run
- ❖ Set **Output predictions** option

Lesson 4.3: Classification by regression

More extensive investigation

Why are we doing this?

- ❖ It's an interesting idea
- ❖ Will lead to quite good performance
- ❖ Leads in to “Logistic regression” (next lesson), with excellent performance
- ❖ Learn some cool techniques with Weka

Strategy

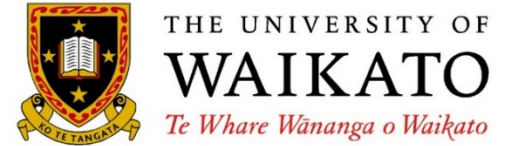
- ❖ Add a new attribute (“classification”) that gives the regression output
- ❖ Use OneR to optimize the split point for the two classes (first restore the class back to its original nominal value)

Lesson 4.3: Classification by regression

- ❖ Supervised attribute filter **AddClassification**
 - choose *functions>LinearRegression* as classifier
 - set *outputClassification* to *true*
 - Apply; adds new attribute called “*classification*”
- ❖ Convert **class** attribute back to nominal
 - unsupervised attribute filter **NumericToNominal**
 - set *attributeIndices* to *9*
 - delete all the other attributes
- ❖ Classify panel
 - unset *Output predictions* option
 - change prediction from *(Num) classification* to *(Nom) class*
- ❖ Select **rules>OneR**; run it
 - rule is based on *classification* attribute, but it's complex
- ❖ Change **minBucketSize** parameter from 6 to 100
 - simpler rule (threshold 0.47) that performs quite well: 76.8%

Lesson 4.3: Classification by regression

- ❖ Extend linear regression to classification
 - *Easy with two classes*
 - *Else use multi-response linear regression, or pairwise linear regression*
- ❖ Also learned about
 - *Unsupervised attribute filter **NominalToBinary**, **NumericToNominal***
 - *Supervised attribute filter **AddClassification***
 - *Setting/unsetting the class*
 - *OneR's **minBucketSize** parameter*
- ❖ But we can do better: Logistic regression
 - *next lesson*



Data Mining with Weka

Class 4 – Lesson 4

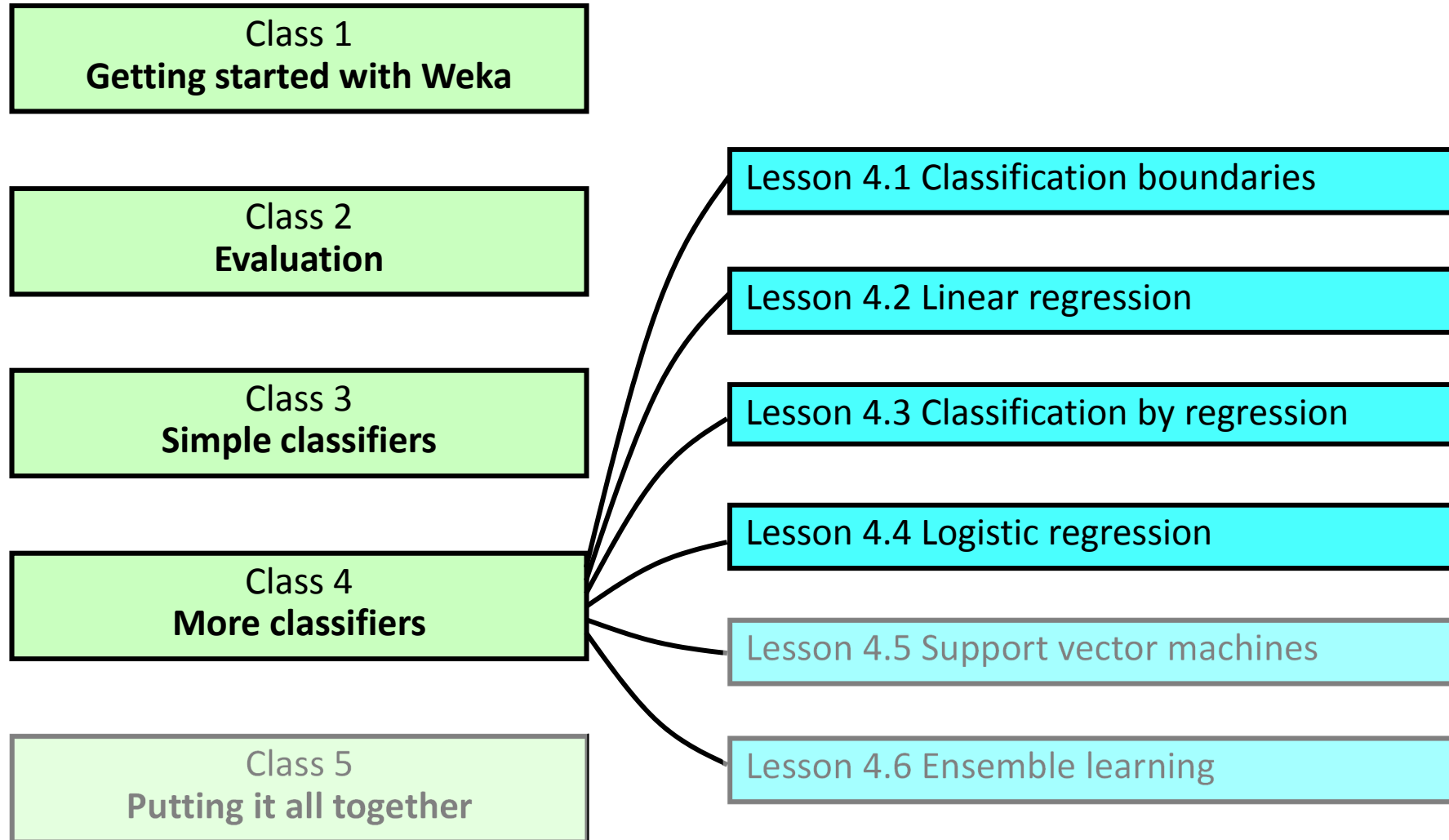
Logistic regression

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Lesson 4.4: Logistic regression



Lesson 4.4: Logistic regression

Can do better by using prediction probabilities

Probabilities are often useful anyway ...

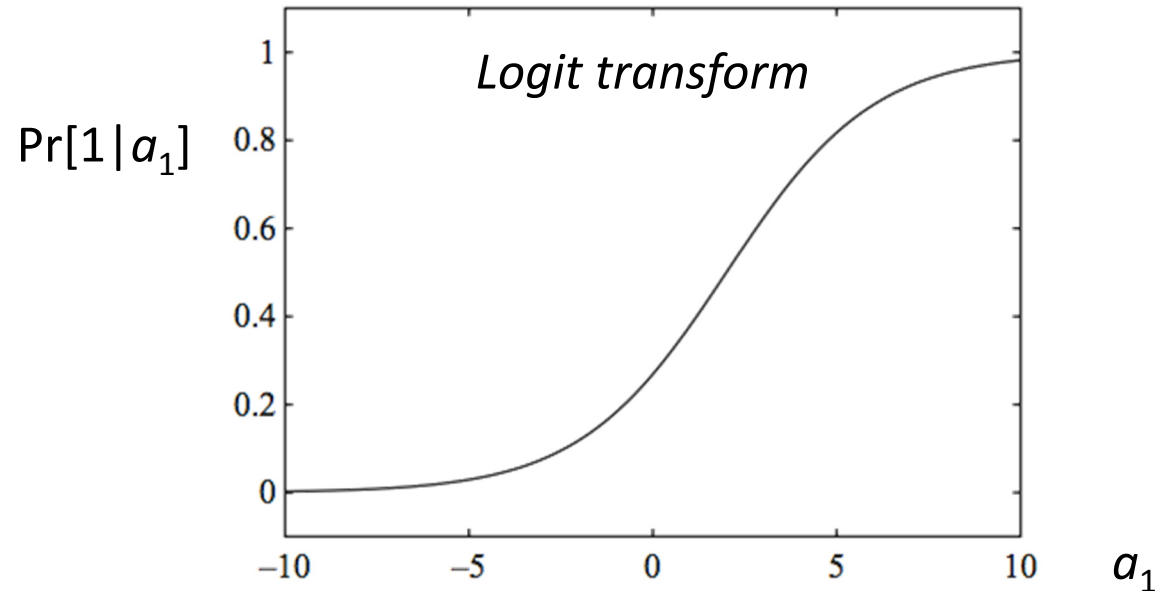
- ❖ Naïve Bayes produces them (obviously)
 - Open **diabetes.arff** and run **Bayes>NaiveBayes** with 90% percentage split
 - Look at columns: *actual, predicted, error, prob distribution*
- ❖ Other methods produce them too ...
 - Run **rules>ZeroR**. Why probabilities [0.648, 0.352] for [tested_negative, tested_positive]?
 - 90% training fold has 448 negative, 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

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



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

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

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%

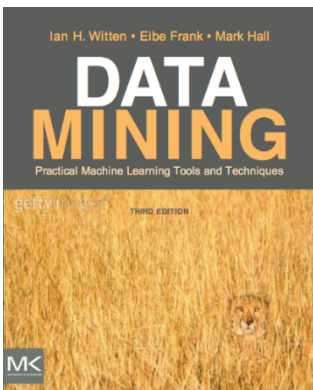
- ❖ Extension to multiple classes ...
 - Perform a regression for each class?
 (like multi-response regression)
 - No. Probabilities won't sum to 1
 - Can be tackled as a joint optimization problem

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 5

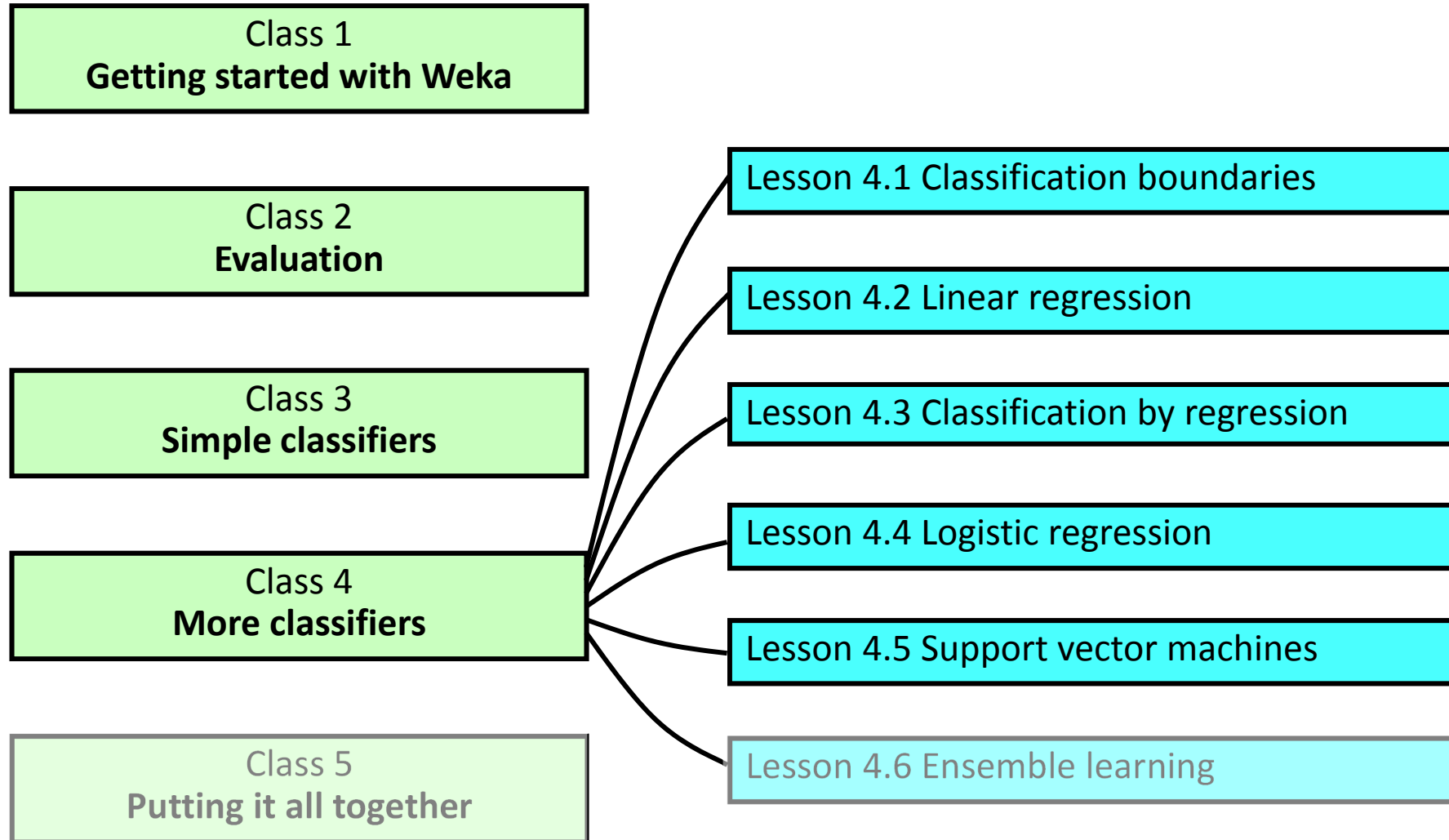
Support vector machines

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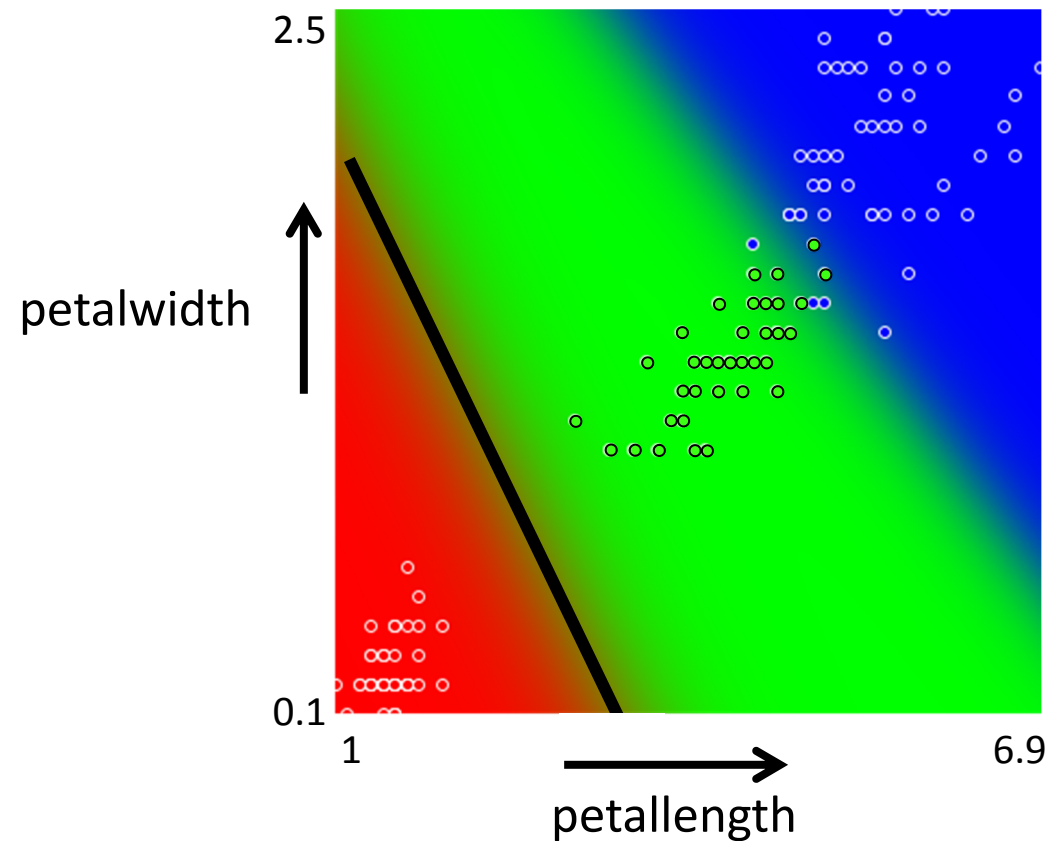
Lesson 4.5 Support vector machines



Lesson 4.5 Support vector machines

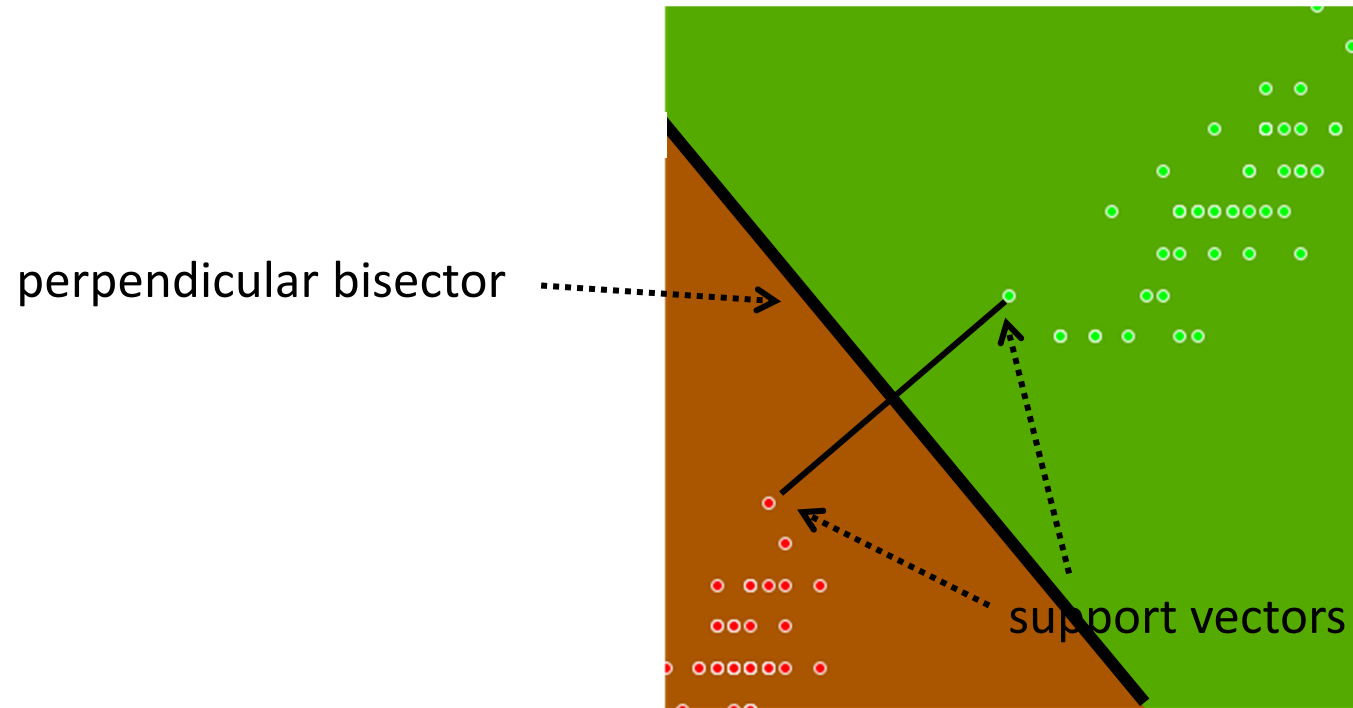
Logistic regression \Rightarrow linear boundaries

- ❖ Weka's boundary visualizer
 - *from the activity following Lesson 3.6*



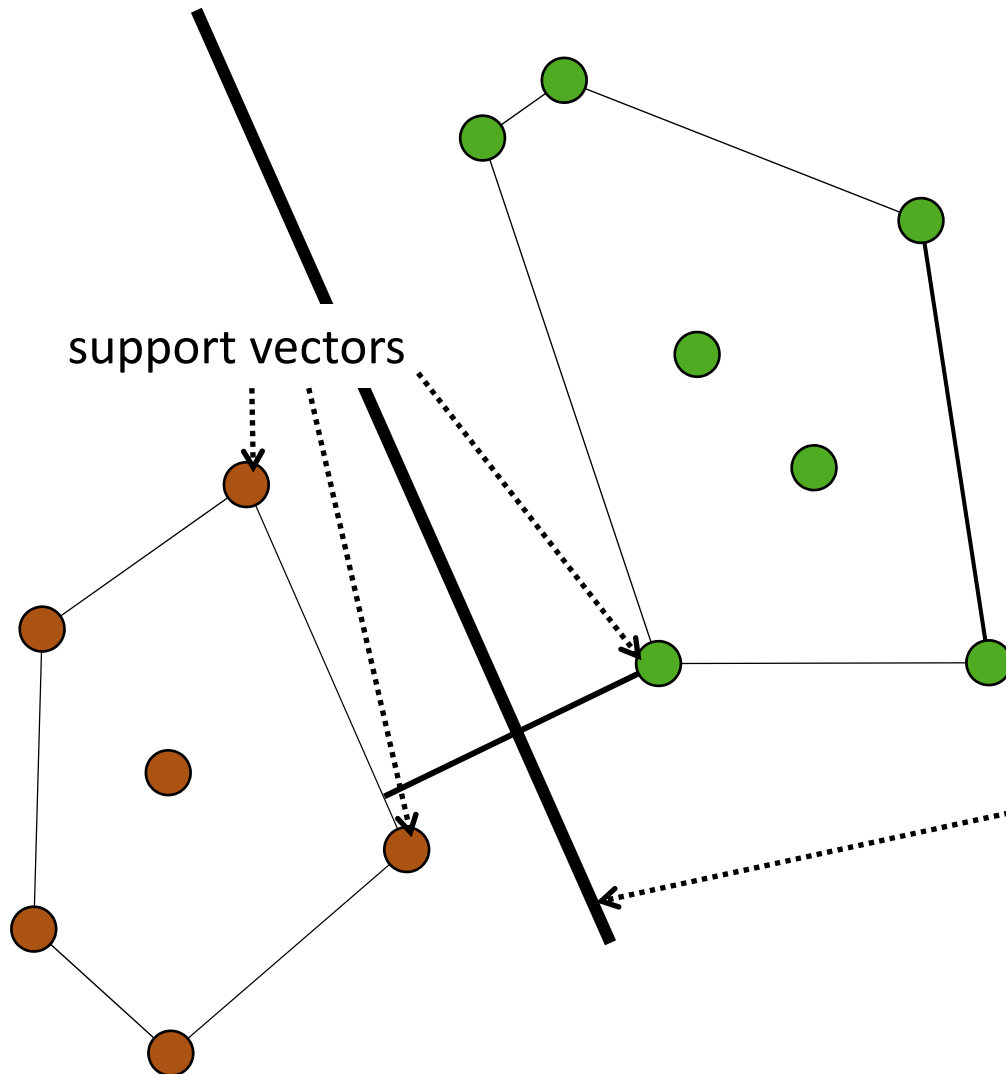
Lesson 4.5 Support vector machines

Support vector geometry



Lesson 4.5 Support vector machines

Maximum margin hyperplane



Support vectors define the boundary
*All other instances can be deleted
without changing it!*

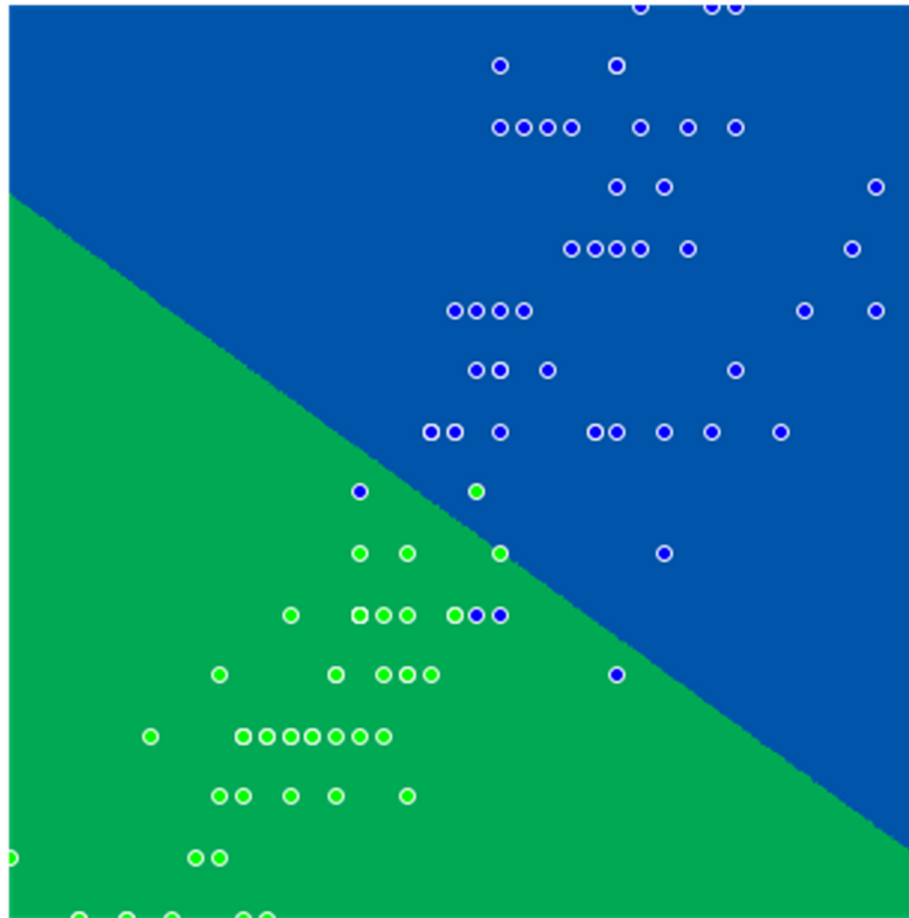
$$x = b + \sum \alpha_i y_i \mathbf{a}(\mathbf{i}) \cdot \mathbf{a}$$

↑
sum over support
vectors $\mathbf{a}(\mathbf{i})$

Lesson 4.5 Support vector machines

Classes that are not linearly separable

(more complex)



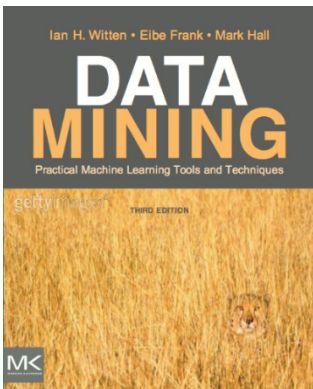
Lesson 4.5 Support vector machines

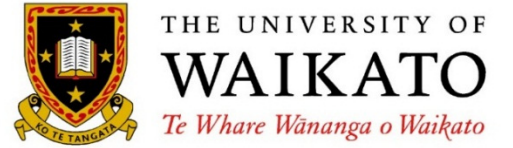
- ❖ Linear decision boundary
 - but can get more complex boundaries with the “Kernel trick”
- ❖ Very resilient to overfitting
 - boundary depends on a very few points
- ❖ Weka: **functions>SMO**
 - restricted to two classes
 - so use Multiresponse linear regression ... or Pairwise linear regression

- ❖ Weka: **functions>LibSVM**
 - External library for support vector machines
 - faster than SMO, more sophisticated options

Course text

- ❖ Section 6.4 *Maximum-margin hyperplane*





Data Mining with Weka

Class 4 – Lesson 6

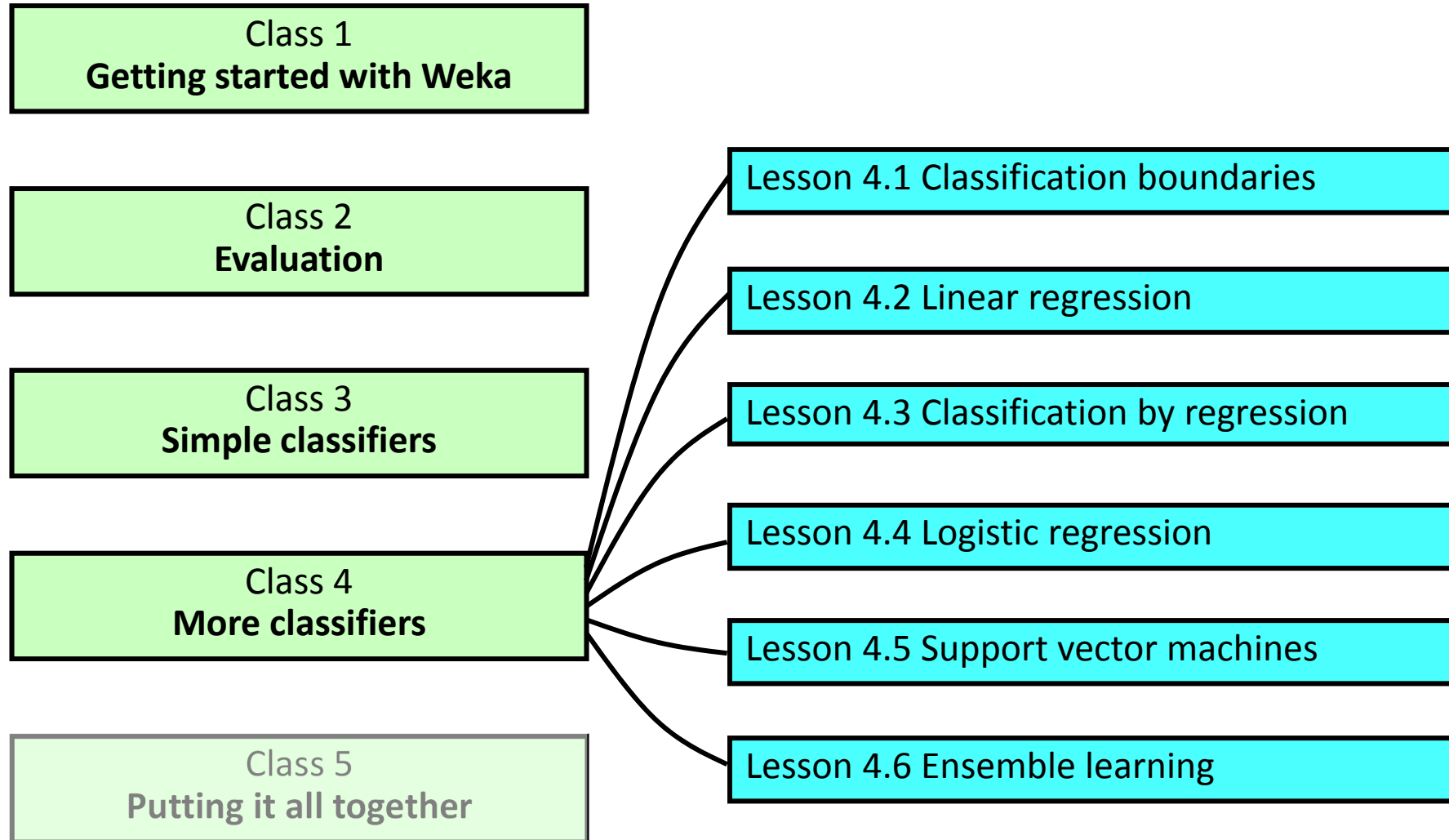
Ensemble learning

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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

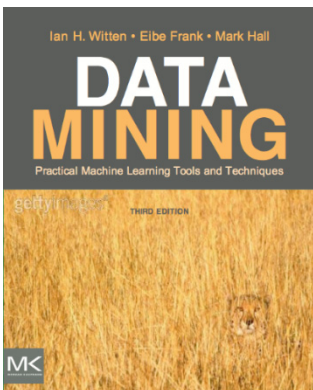
- ❖ Combine predictions of base learners using a *meta learner* (not voting)
 - *base learners: level-0 models*
 - *meta learner: level-1 model*
 - *predictions of base learners are input to meta learner*
- ❖ Base learners are usually different schemes
- ❖ Can't use predictions on training data to generate 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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