A Novel Empirical Approach to the Defect Content Estimation Problem for Software Inspections

Frank Padberg

Universität Karlsruhe

Germany

Motivation

- not all defects are detected during an inspection
- total number of defects is not known exactly
- number of defects is an important management tool (cf. prescribed level of defect-freeness)

© Dr. Frank Padberg 2003

Motivation

- not all defects are detected during an inspection
- total number of defects is not known exactly
- number of defects is an important management tool (cf. prescribed level of defect-freeness)
- reliably estimate the number of defects in a software document from the outcome of an inspection!

© Dr. Frank Padberg 2003

Inspection Outcome

- list of detected defects
- zero-one matrix: shows which reviewer detected which defect
- classification of the defects

© Dr. Frank Padberg 2003

Existing Estimation Methods

- capture–recapture methods (Eick ea. ICSE 1992)
- curve–fitting methods (Wohlin ea. ICSE 1998)
- studies show that estimates are far too unreliable to be useful in engineering practice (Briand ea. TSE 2000, Biffl ea. ICSE 2001)

© Dr. Frank Padberg 2003

Sample Database

- 16 inspections from controlled experiments at NASA SEL (Basili ea. 1994/1995)
- specification documents of varying size
- between 6 and 8 reviewers
- true number of defects known exactly
- serves as standard benchmark

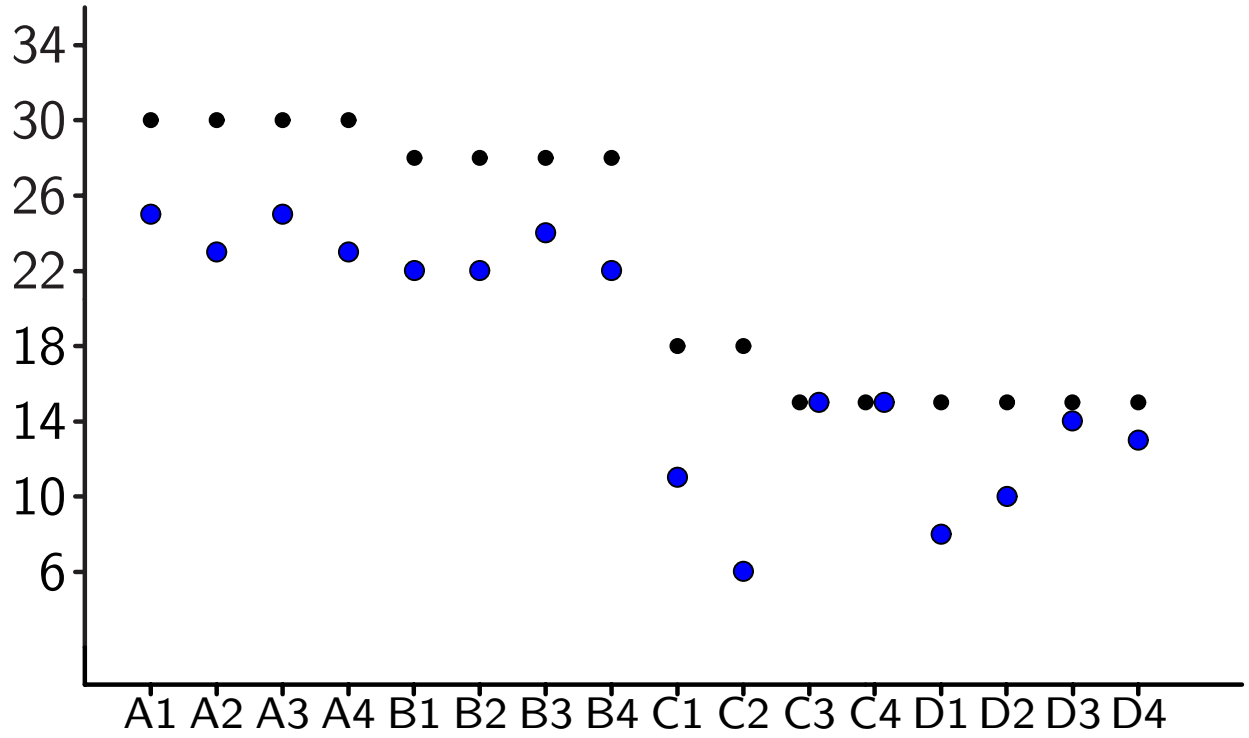
© Dr. Frank Padberg 2003

Input Data for Capture–Recapture

- inspection viewed as a short test series
- number w_k of defects detected by reviewer k
- total number d of different defects detected
- example: $(\,9,\,7,\,6,\,13,\,9,\,6\,)$ and $d = 23$

© Dr. Frank Padberg 2003

Capture–Recapture Estimates

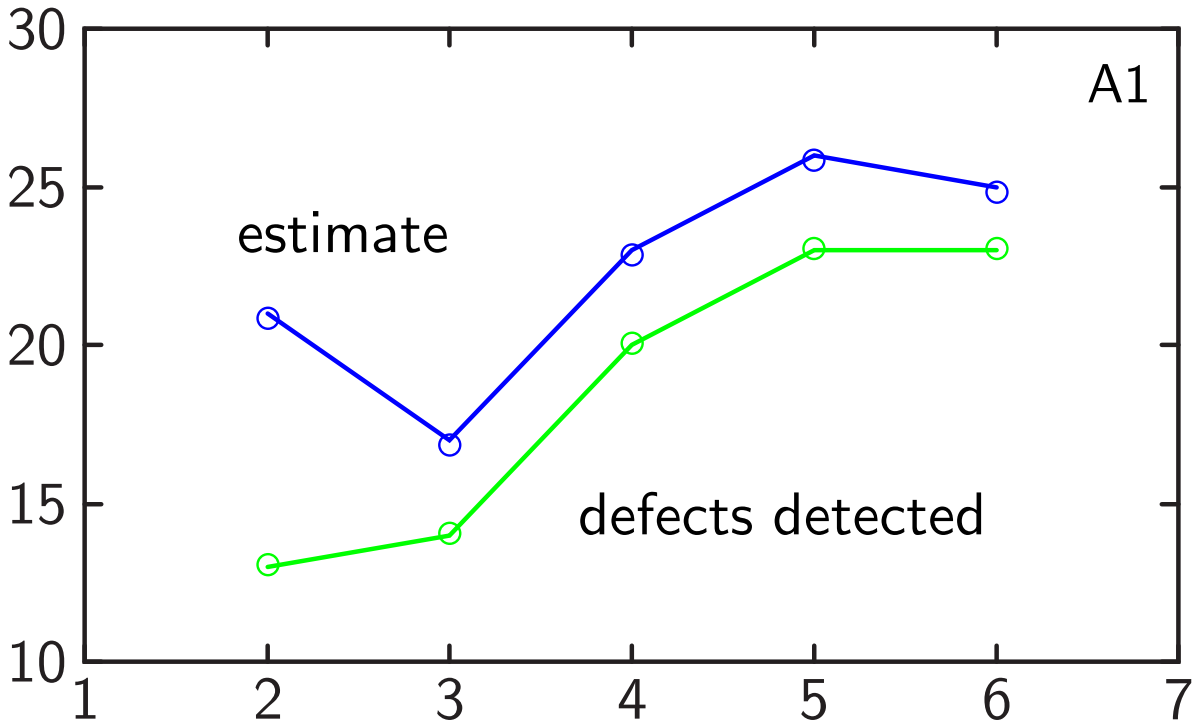


mean abs. error of 24 percent

max error of −67 percent

© Dr. Frank Padberg 2003

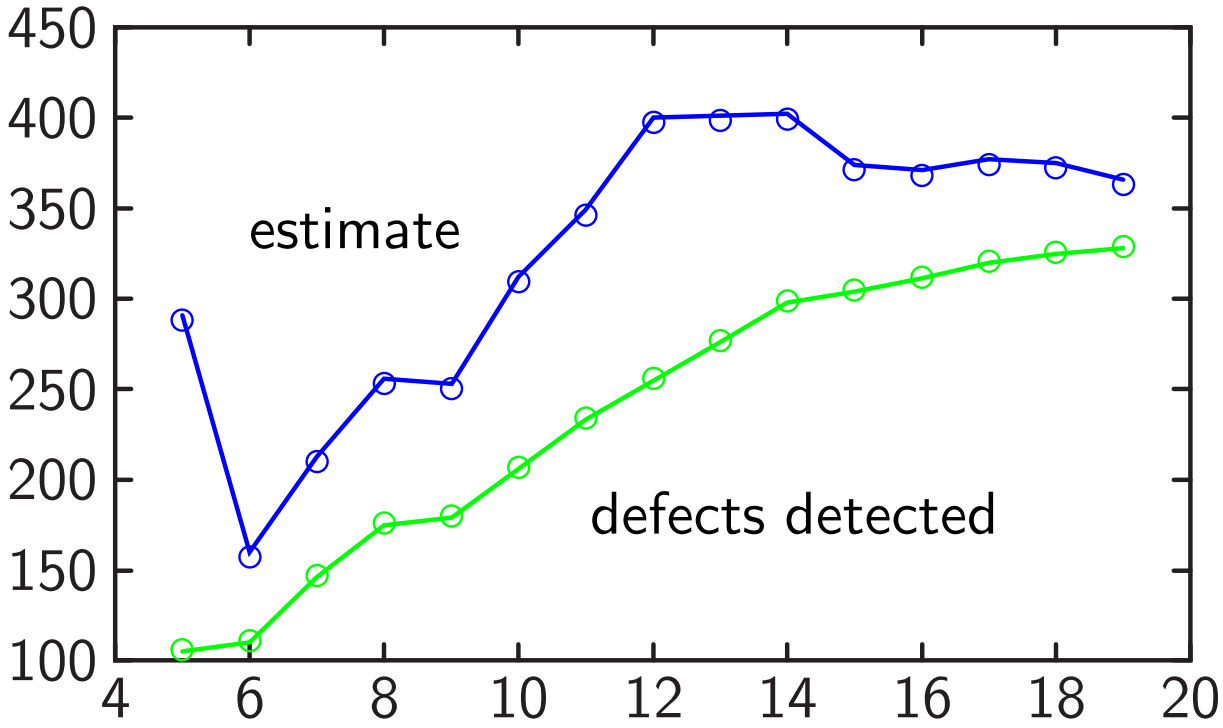
CR–Estimate versus Number of Reviewers



estimates vary with the number of reviewers;
final estimate too low (25 instead of 30)

© Dr. Frank Padberg 2003

Cap-Recap Estimate Versus Test Series Length

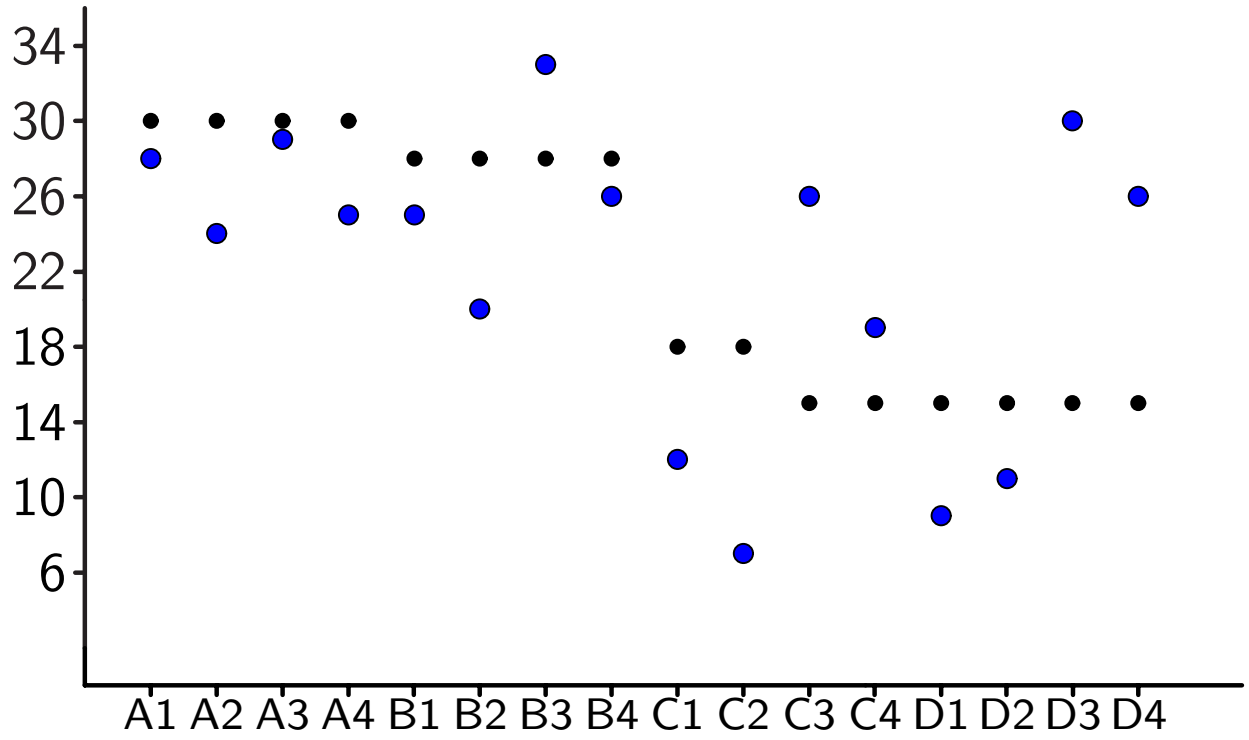


some test series of length 19

estimate needs some time to stabilize!

© Dr. Frank Padberg 2003

Estimates for Detection Profile Method



mean abs. error of 36 percent

extremely high variation

© Dr. Frank Padberg 2003

Why Capture–Recapture Fails

- mathematics: "test series" is too short

© Dr. Frank Padberg 2003

Why Capture–Recapture Fails

- mathematics: "test series" is too short
- only the outcome of the current inspection enters the estimation

© Dr. Frank Padberg 2003

Why Capture–Recapture Fails

- mathematics: "test series" is too short
- only the outcome of the current inspection enters the estimation
- in other words: no learning from experience

© Dr. Frank Padberg 2003

Machine Learning Approach

- use empirical data about past inspections for estimating
- learn relationship between observable features of an inspection and true number of defects contained in the document

© Dr. Frank Padberg 2003

Machine Learning Approach

- use empirical data about past inspections for estimating
- learn relationship between observable features of an inspection and true number of defects contained in the document
- view defect content estimation as a regression problem

© Dr. Frank Padberg 2003

Required Inspection Data

- zero-one matrix
- document meta-data:

  type, size, complexity, ...
- inspection meta-data:

  reading technique, number of reviewers, ...
- true number of defects

© Dr. Frank Padberg 2003

Steps to Take

1. collect empirical inspection data
2. choose features
3. choose regression technique
4. possibly subdivide database (meta-data)
5. do the regression (machine learning)

© Dr. Frank Padberg 2003

Building a Database

- collect data from as many inspections as possible (inspection outcome and meta-data)
- trace defects which are detected in later phases (including maintenance) back to the corresponding document
- compute approximate value for true number of defects for each document in the database

© Dr. Frank Padberg 2003

Candidate Features

- derived from zero–one matrix
- TDD, AVE, MIN, MAX, STD
- example A1:

  (9, 7, 6, 13, 9, 6) and 23 yields

TDD	AVE	MIN	MAX	STD
23	8.3	6	13	2.4

© Dr. Frank Padberg 2003

Input Data for Linear Regression

- correlation analysis yields ranking

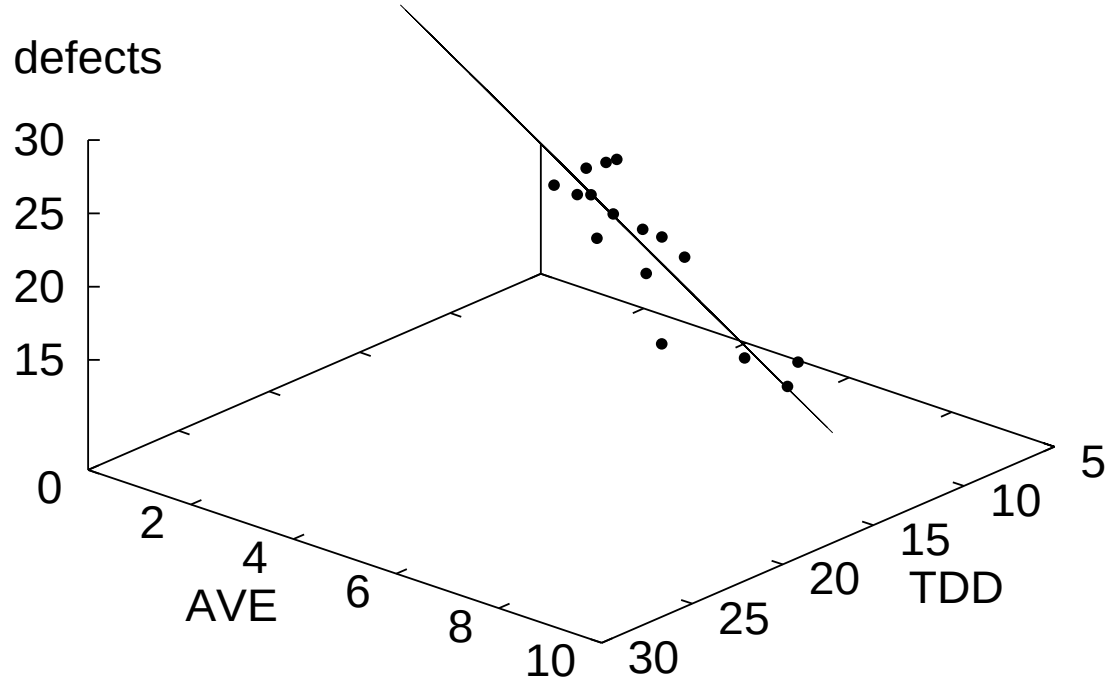
  TDD > AVE > MIN > MAX > STD

- some datapoints:

inspection	TDD	AVE	target
A1	23	8.3	30
B1	20	6.0	28
C1	10	3.2	18
D1	6	1.3	15

© Dr. Frank Padberg 2003

Regression Hyperplane



all 16 inspections

some points have large distance to hyperplane

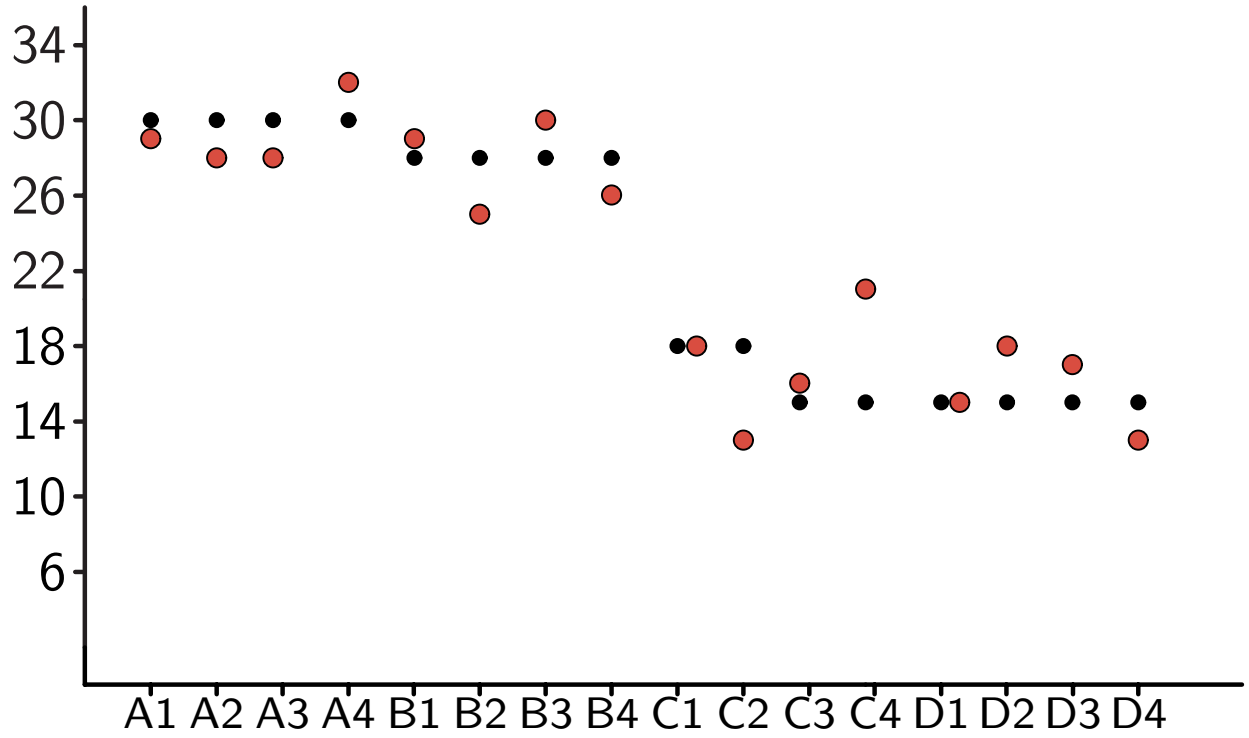
© Dr. Frank Padberg 2003

Jackknife Validation

- leave out an inspection from the database
- compute the regression hyperplane using the remaining 15 inspections
- compute the regression estimate for the one inspection which was left out
- compare the estimate with the true value

© Dr. Frank Padberg 2003

Linear Regression Estimates

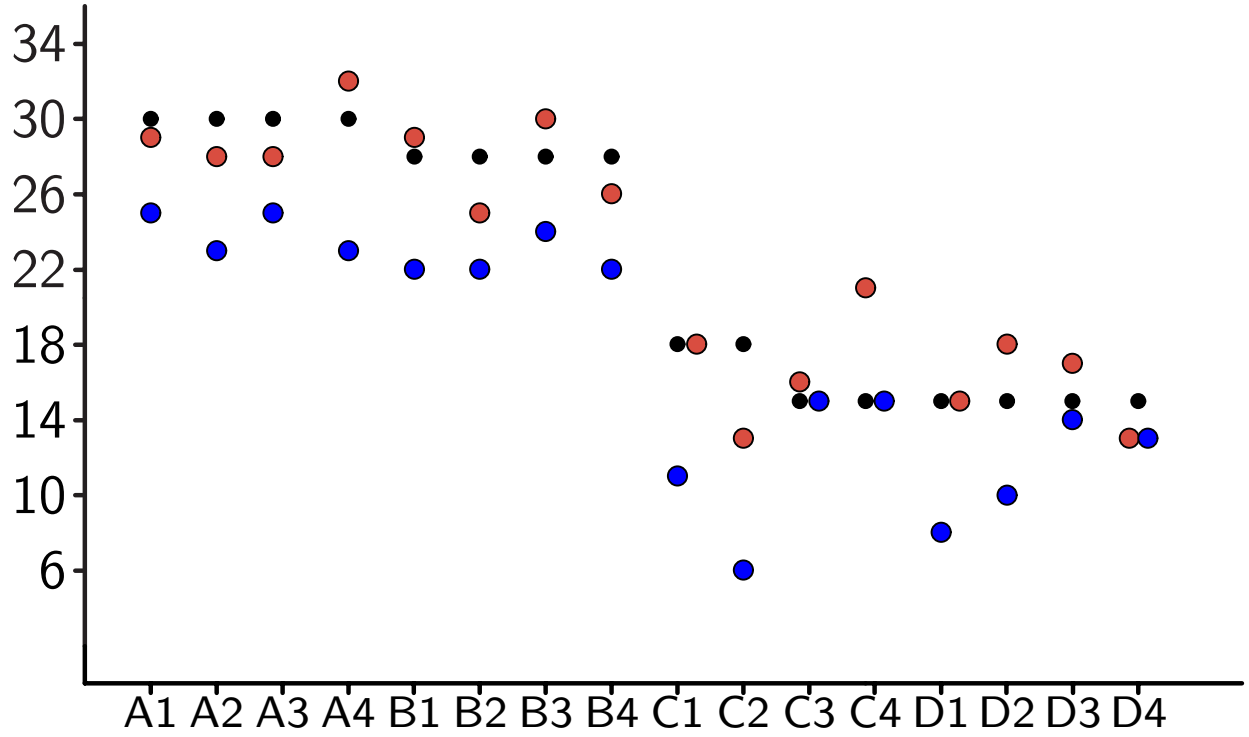


jackknife error of 11 percent

max error of 40 percent

© Dr. Frank Padberg 2003

Linear Regression versus Capture–Recapture



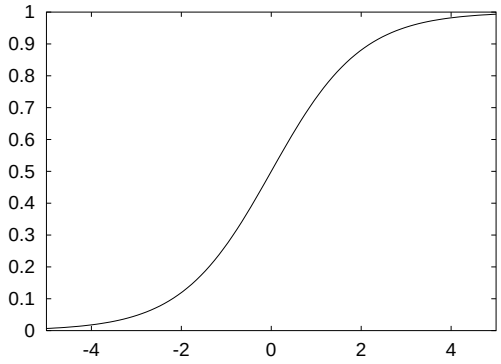
clearly outperforms capture–recapture!

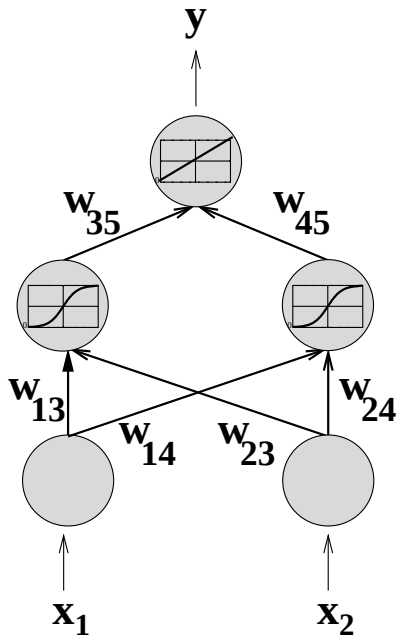
(11 percent versus 24)

© Dr. Frank Padberg 2003

Non-Linear Regression: Neural Networks

$$\text{logist}\,(\,x\,) \;=\; \frac{1}{1\;+\;e^{-x}} \qquad\qquad s_i \;=\; \text{logist}\Big(\sum_j w_{ji}\cdot s_j\Big)$$





© Dr. Frank Padberg 2003

Neural Network Topology

- number of inputs
- number of hidden layers
- number of units in hidden layers
- connections between layers

© Dr. Frank Padberg 2003

Training a Neural Network

- fit regression function to training data
- non-linear optimization process (choose weights to minimize error on training data)
- no simple formula
- might get caught in local minimum
- train networks with different initial weights

© Dr. Frank Padberg 2003

Input Data for Non-Linear Regression

- non-linear feature selection yields ranking

  TDD > STD > MAX > MIN > AVE

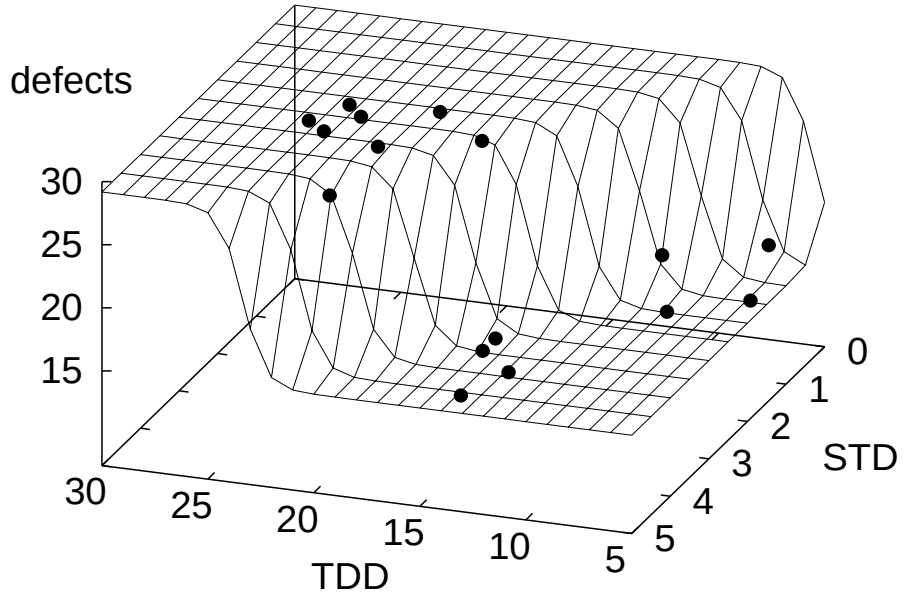
- STD instead of AVE

- some training patterns:

inspection	TDD	STD	target
A1	23	2.4	30
B1	20	1.7	28
C1	10	1.5	18
D1	6	1.4	15

© Dr. Frank Padberg 2003

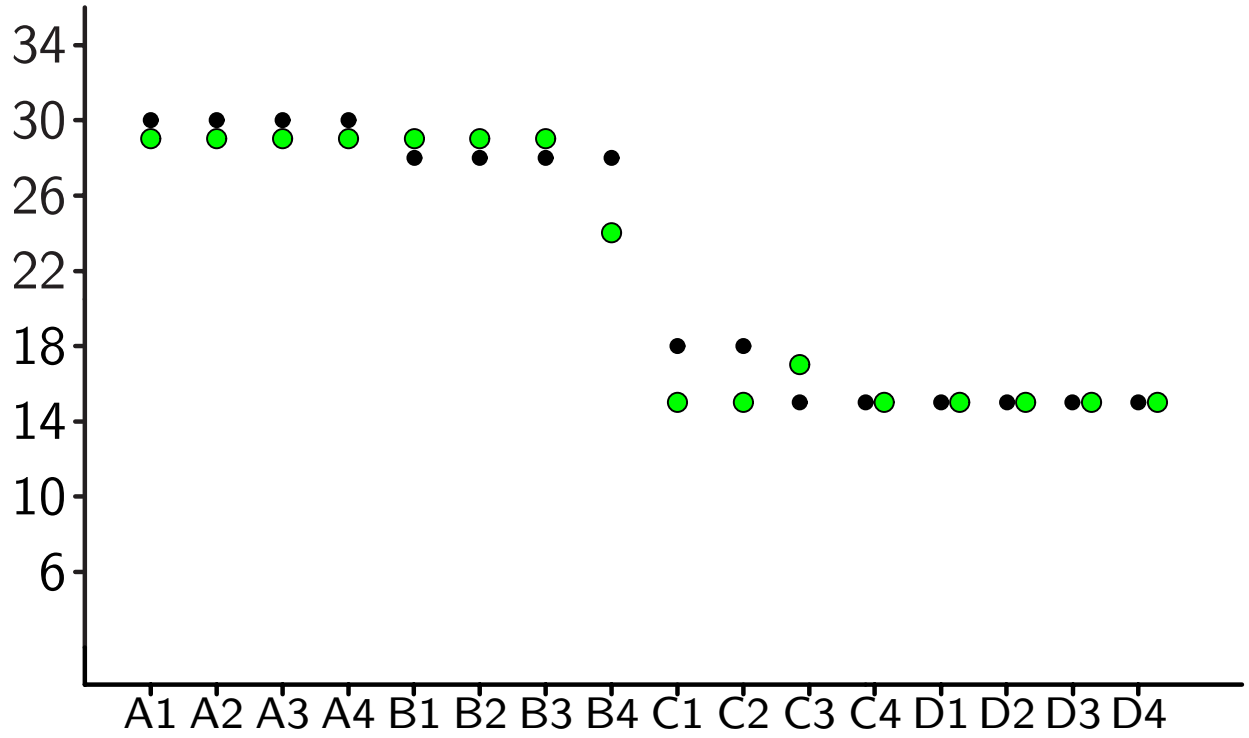
Non-Linear Regression Surface



two hidden units in one layer; all 16 inspections surface fits data very well

© Dr. Frank Padberg 2003

Neural Network Estimates

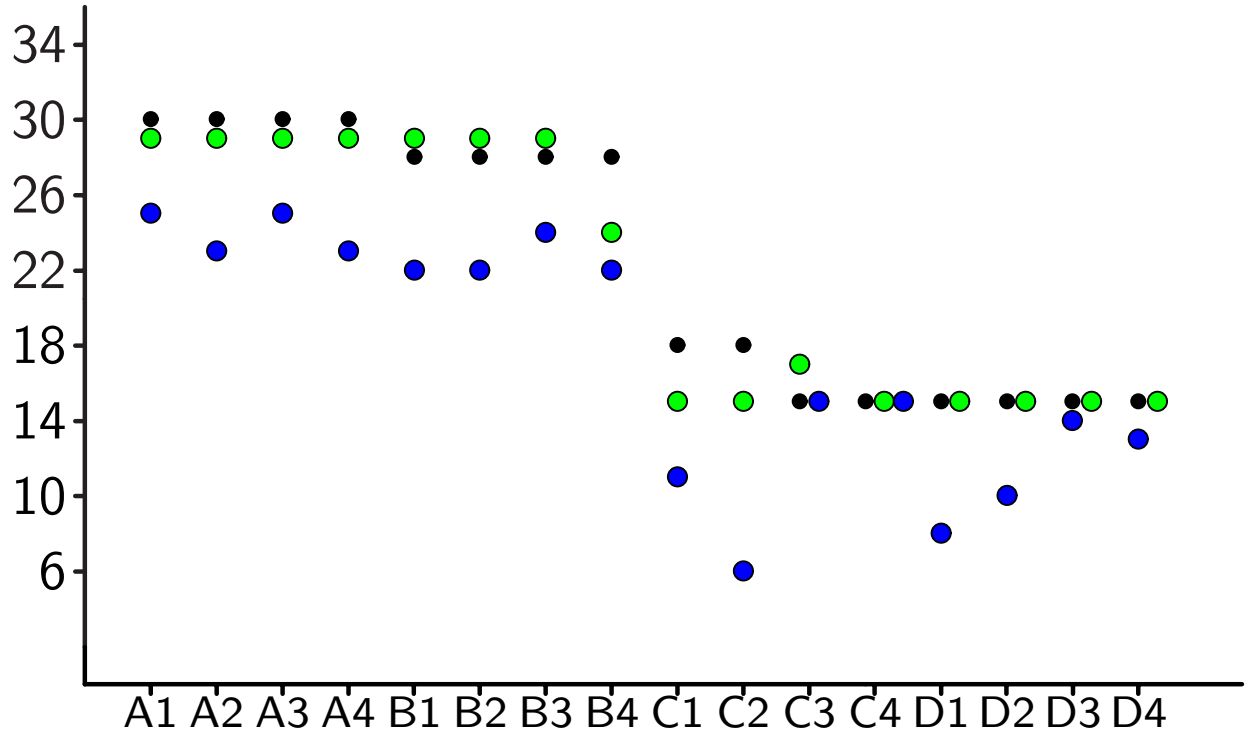


jackknife error of 6 percent

max error of −17 percent

© Dr. Frank Padberg 2003

Neural Networks versus Capture–Recapture

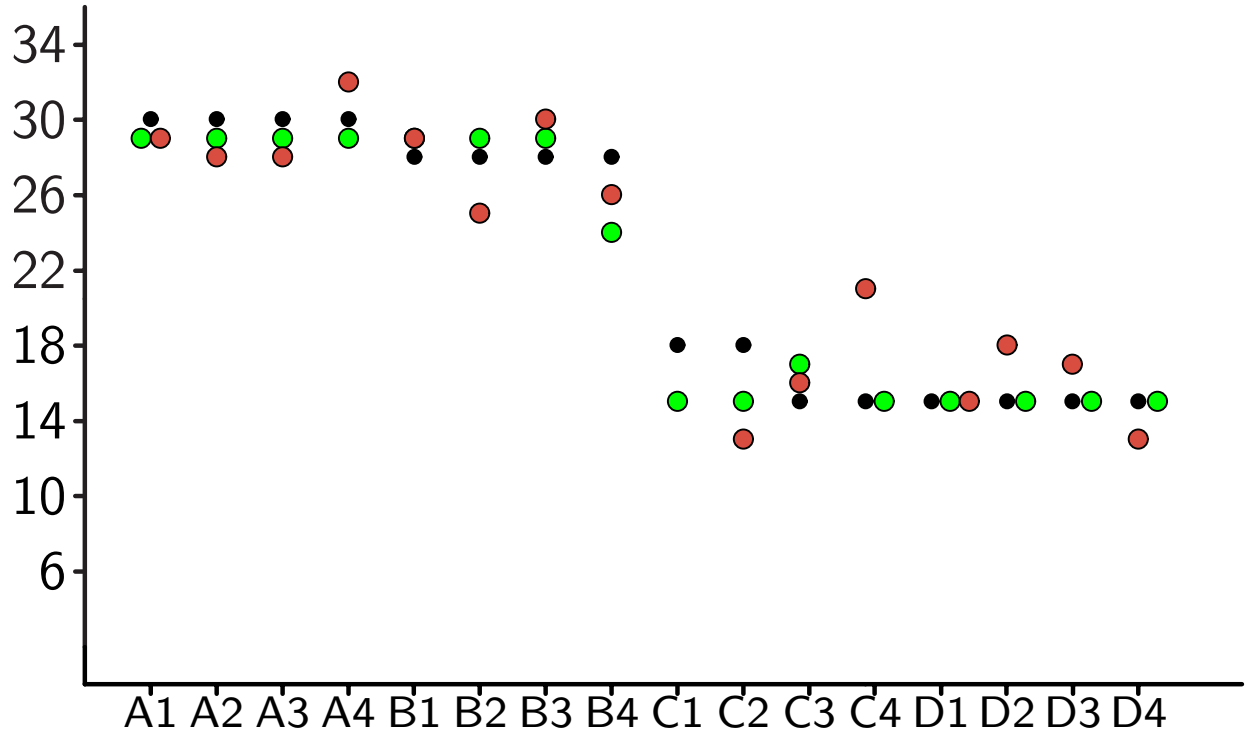


clearly outperforms capture–recapture!

(6 percent versus 24)

© Dr. Frank Padberg 2003

Neural Networks versus Linear Regression



outperforms linear regression

(6 percent versus 11 ; smaller variance)

© Dr. Frank Padberg 2003

Neural Network Advantages

- much flexibility when fitting to data
- detects non-linearity in the data
- gives guidelines which features to use

© Dr. Frank Padberg 2003

Neural Network Advantages

- much flexibility when fitting to data
- detects non-linearity in the data
- gives guidelines which features to use
- worked well with small benchmark dataset
- automatically adapted to different document types and sizes

© Dr. Frank Padberg 2003

Result Summary

Method	mean abs. error	max error
Capture–Recapture	24 %	−67 %
Detection Profile	36 %	113 %
Linear Regression	11 %	40 %
Interval Estimates	(7 %)	(14 %)
Neural Networks	6 %	−17 %

novel approaches are promising!

need more empirical data for validation

© Dr. Frank Padberg 2003

Own Publications About the Defect Content Estimation Problem

- *Empirical Interval Estimates for the Defect Content After an Inspection*
  International Conference on Software Engineering ICSE (2002)

- *Applying Machine Learning to Solve an Estimation Problem in Software Inspections*
  International Conference on Artificial Neural Networks ICANN (2002) (with T. Ragg and R. Schoknecht)
  accepted for Transactions on Software Engineering TSE

© Dr. Frank Padberg 2003

Own Publications (cont.)

- *A Fast Algorithm to Compute Maximum Likelihood Estimates for the Hypergeometric Software Reliability Model*
  Asia-Pacific Conference on Quality Software APAQS (2001)

- *Maximum Likelihood Estimates for the Hypergeometric Software Reliability Model*
  International Journal of Reliability, Quality and Safety Engineering IJRQSE (2003)

© Dr. Frank Padberg 2003

Thank You !

© Dr. Frank Padberg 2003