Imputing the epigenome

http://sahirbhatnagar.com/talks/

March 12, 2015

(Ernst and Kellis 2015)

Main Idea

Matrix of Observed and Imputed Data

1. Leverage other marks in same sample

2. Leverage same mark in different sample

Types of data used to impute

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- Chromatin state annotation

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- When the target mark has been mapped in only a few samples, the features pertaining to the same mark in other samples may be less informative or more biased e.g. TFBS
- For tissue samples that reflect mixtures of multiple cell types, our imputed maps will most likely reflect the same mixture as the observed data, though deconvolution of mixed samples is a potentially important direction for future work

ChromImpute Software

- Command line tool written in `JAVA`
- http://www.biolchem.ucla.edu/labs/ernst/ChromImpute/

Not a new idea

Leo Breiman (1928-2005)

(Breiman 2001)

`randomForest` package in R

MissForest

(Stekhoven and Bühlmann 2012)

`missForest` package in `R`

Introduction to Regression Trees

Some intuition behind the imputation approach

```
total sales = 7.1 + 0.0475 x # of TV's sold
```

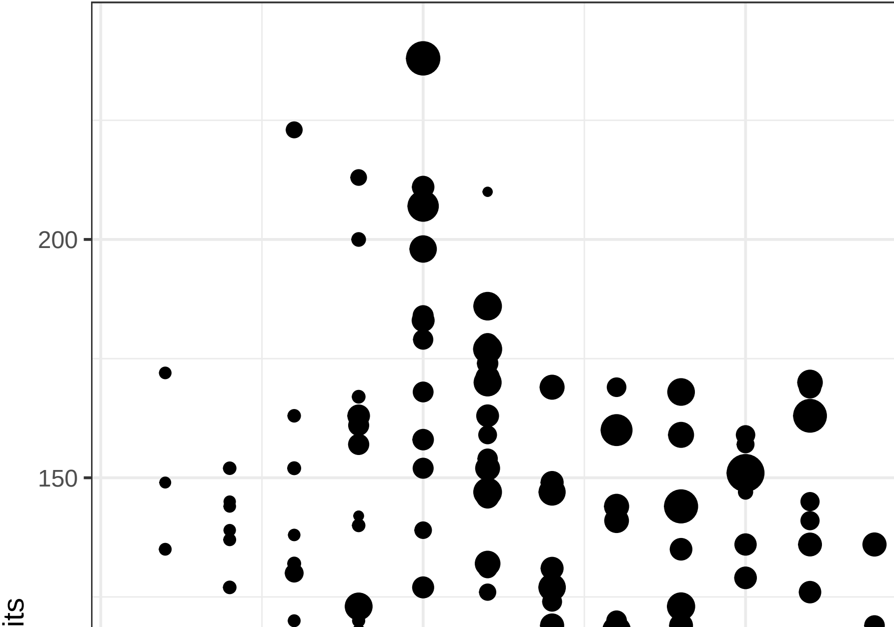
Tree-based Methods

- Involves *splitting* the predictor space into simple regions
- Since the set of splitting rules used to segment the predictor space can be summarized in a tree, these types of approaches are known as decision-tree methods (James et al. 2013)

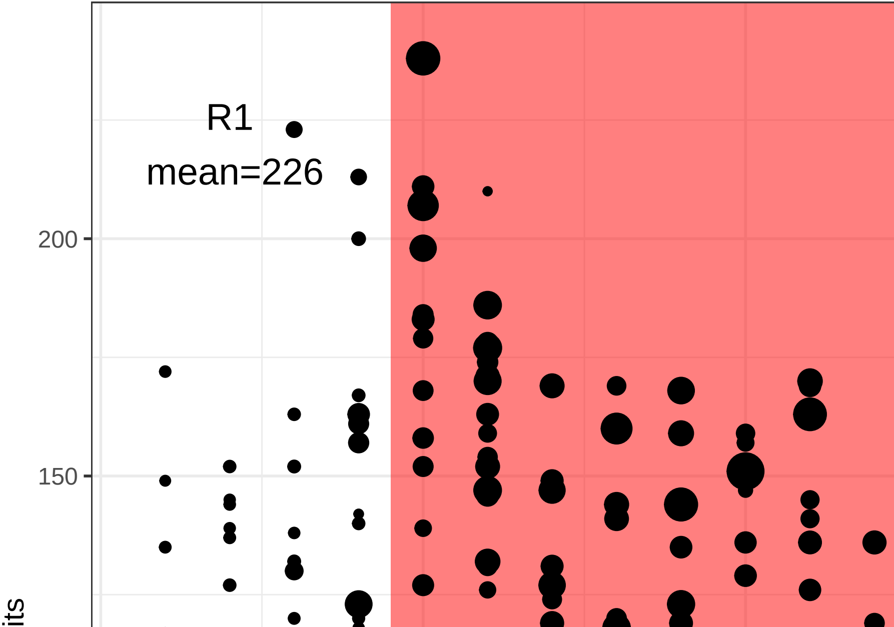
Baseball Data

```
## PhantomJS not found. You can install it with webshot::ir
```

Predict salary based on Hits and Years Played



How to split the data



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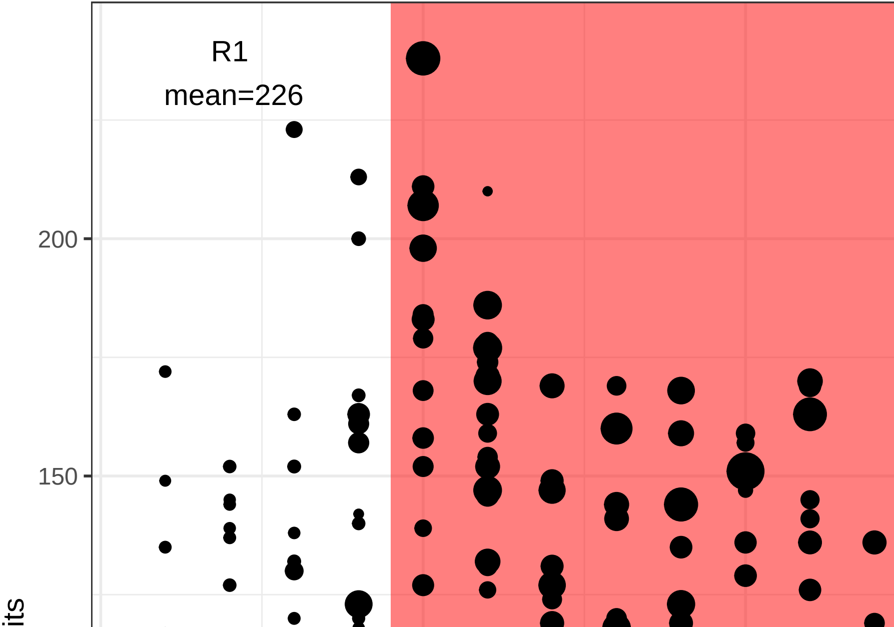

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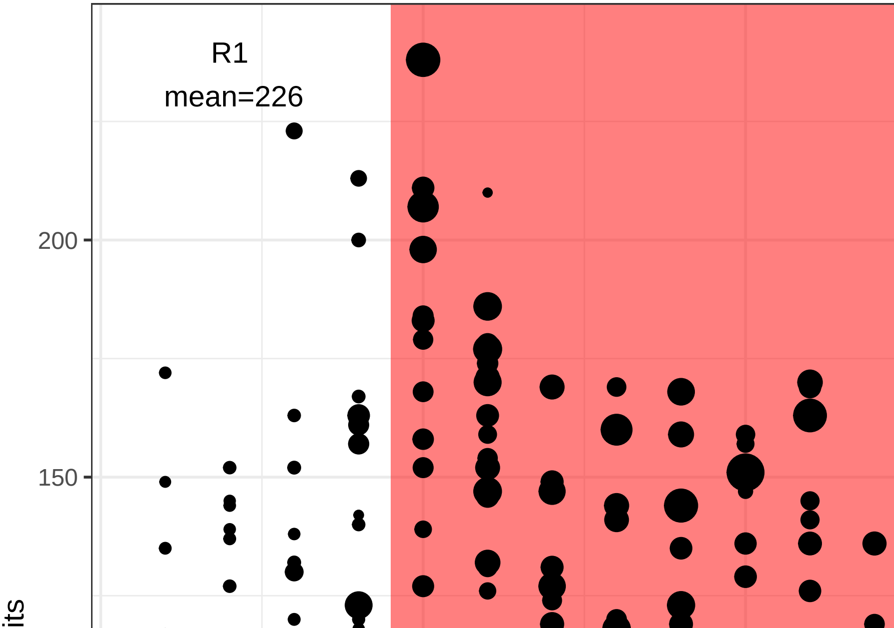

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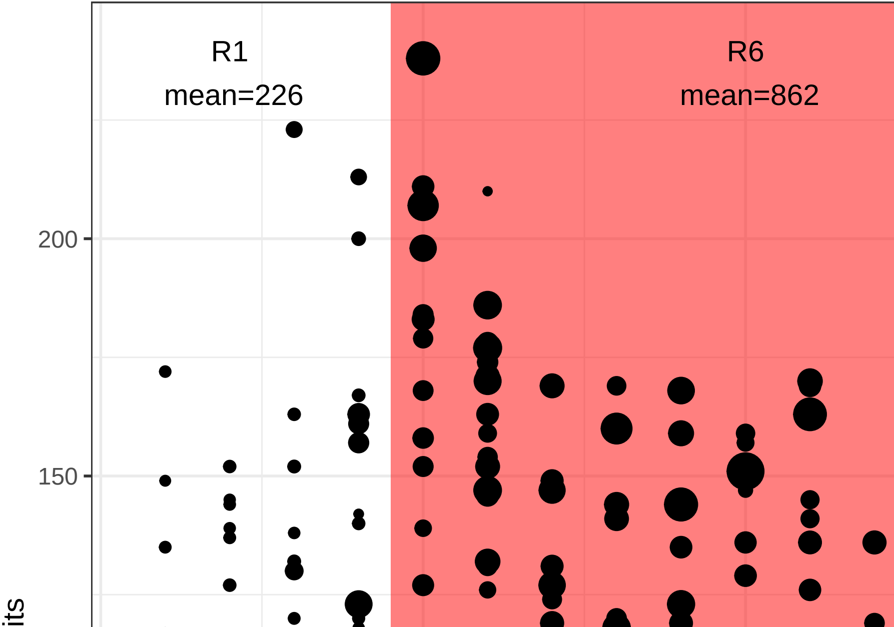
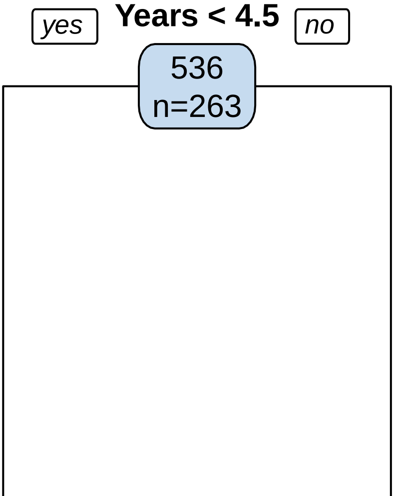


Regression Tree for Baseball data

```
## Warning: Bad 'data' field in model 'call' (expected a da
## To silence this warning:
##     Call rpart.plot with roundint=FALSE,
##     or rebuild the rpart model with model=TRUE.
```



Decision Tree

More Details of Tree Building

- The goal is to find boxes $R_1, \ldots, R_J$ that minimize the residual sum of squares give by

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- Begins at the top, and never looks back

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- Solution: Combining a large number of trees can often result in dramatic improvements in prediction accuracy, at the expense of some loss interpretation.

Bagging

The Bootstrap

(James et al. 2013)

Pull yourself up by your bootstraps

Random Forests

ETH Zurich Slides

Acknowledgements

Regression tree slides are based on

Free PDF book

Leo Breiman (1928-2005)

References

```
## No encoding supplied: defaulting to UTF-8.
```


Breiman, Leo. 2001. "Random Forests." *Mach. Learn.* 45 (1). Hingham, MA, USA: Kluwer Academic Publishers: 5–32. https://doi.org/10.1023/A:1010933404324.

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