Labeled anomalies

ANOMALY DETECTION IN R

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Satellite image data

```
head(sat, 5)
```

```
  label V1  V2  V3 V4 V5
1     0 92 115 120 94 84
2     0 84 102 106 79 84
3     0 84 102 102 83 80
4     0 80 102 102 79 84
5     0 84  94 102 79 80
```

Satellite image data

```
table(sat$label)
```

```
   0    1
5732   71
```

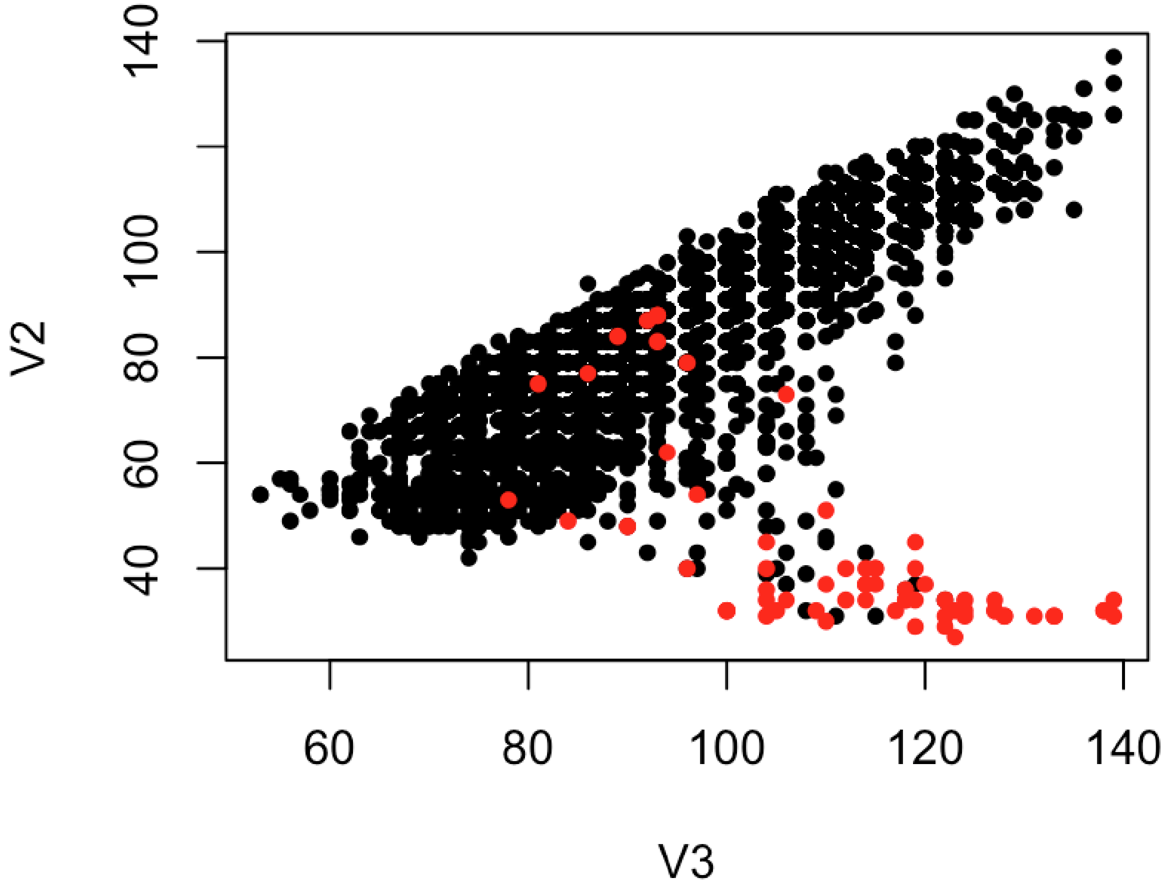
Cotton crop image proportion:

```
71 / 5803
```

```
0.01223505
```

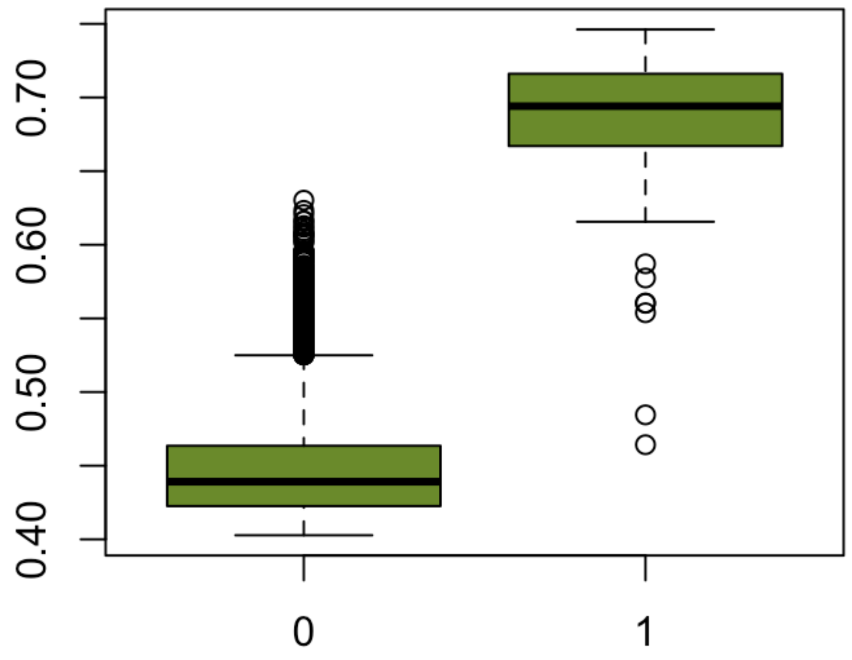
Visualize true anomalies

```
plot(V2 ~ V3, data = sat, col = as.factor(label), pch = 20)
```



Anomaly score versus true label

```
sat_for <- iForest(sat[, -1], nt = 100)
sat$score <- predict(sat_for, features)
boxplot(score ~ label, data = sat, col = "olivedrab4")
```



Why not use models to predict labels?

Example 1: Detecting rare disease cases

- Too few cases

Example 2: Credit card fraud

- Changes rapidly

Let's practice!

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Measuring performance

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Using a decision threshold

Choose a high value

```
high_score <- quantile(sat$score, probs = 0.99)
high_score
```

```
    99%
0.6228078
```

Binarize score

```
sat$binary_score <- as.numeric(score >= high_score)
```

Tables of agreement

Comparing true label and binarized score

```
table(sat$label, sat$binary_score)
```

```
       0    1
  0 5729    3
  1   15   56
```

- 56 out of 71 anomalies found

Recall

Anomalies correctly identified ÷ Total anomalies

- 1 = Perfect recall; every anomaly detected by algorithm

```
table(sat$label, sat$binary_score)
```

```
     0    1
0 5729    3
1   15   56
```

Precision

Anomalies correctly identified ÷ Total scored as anomalous

- 1 = Perfect precision; no normal instances incorrectly labeled

```
table(sat$label, sat$binary_score)
```

```
       0    1
  0 5729    3
  1   15   56
```

```
precision <- 56 / (56 + 3)
precision
```

```
0.9491525
```

Let's practice!

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Working with categorical features

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Checking column classes

Class of a single column

```
class(sat$V1)
```

```
"numeric"
```

Class of all columns

```
sapply(X = sat, FUN = class)
```

```
      label          V1          V2          V3          V4          V5          V6    high_low
  "numeric"   "numeric"   "numeric"   "numeric"   "numeric"   "numeric"   "numeric" "character"
```

Isolation forest

Encode categorical features as factor

```
sat$high_low <- as.factor(sat$high_low)
class(sat$high_low)
```

```
"factor"
```

Train isolation forest

```
sat_for <- iForest(sat[, -1], nt = 100)
```

LOF with factors

Gower distance measures distance between points with categorical & numeric features

```
library(cluster)
sat_dist <- daisy(sat[, -1], metric = "gower")
```

Pass `sat_dist` to `lof`

```
sat_lof <- lof(sat_dist, k = 10)
```

Exploring Gower distance matrix

- Convert object to matrix

```
sat_distmat <- as.matrix(sat_dist)
```

- Find max and min interpoint distances

```
range(sat_distmat)
```

```
0.0000000 0.8680774
```

Let's practice!

ANOMALY DETECTION IN R

Recap: Anomaly Detection in R

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Course summary

Chapter 1

Testing and visualizing outliers for single variable and time series

Chapter 2

Distance and density based anomaly detection

Chapter 3

Tree based anomaly detection

Chapter 4

Comparing performance and using factors

What's next?

- **Model tuning:** eg. choosing k for LOF & kNN
- **Many other techniques:** One-class SVM & clustering approaches

Congratulations!

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