Time Series Deep Learning

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About Business Science

- We are applications people that build tools to solve tough problems

- We serve the data science community

- We empower organizations
  - Expert plan-based coaching, training, & consultation
  - Specialize in R Package Development, Shiny Apps, and more!
  - NEW!! Business Science University (BSU)

We Love Time Series

Open Source Packages

NEW!!
Anomaly
Detection

anomalize

Most Popular
Financial Data
Stock/Portfolio
Analysis

tidyquant

tibbletime

Time-Aware
tibbles
(dplyr)

Helps Do
Time-Based
Forecasting
w/ forecast

sweep

timetk

Time Series
ML

Objectives

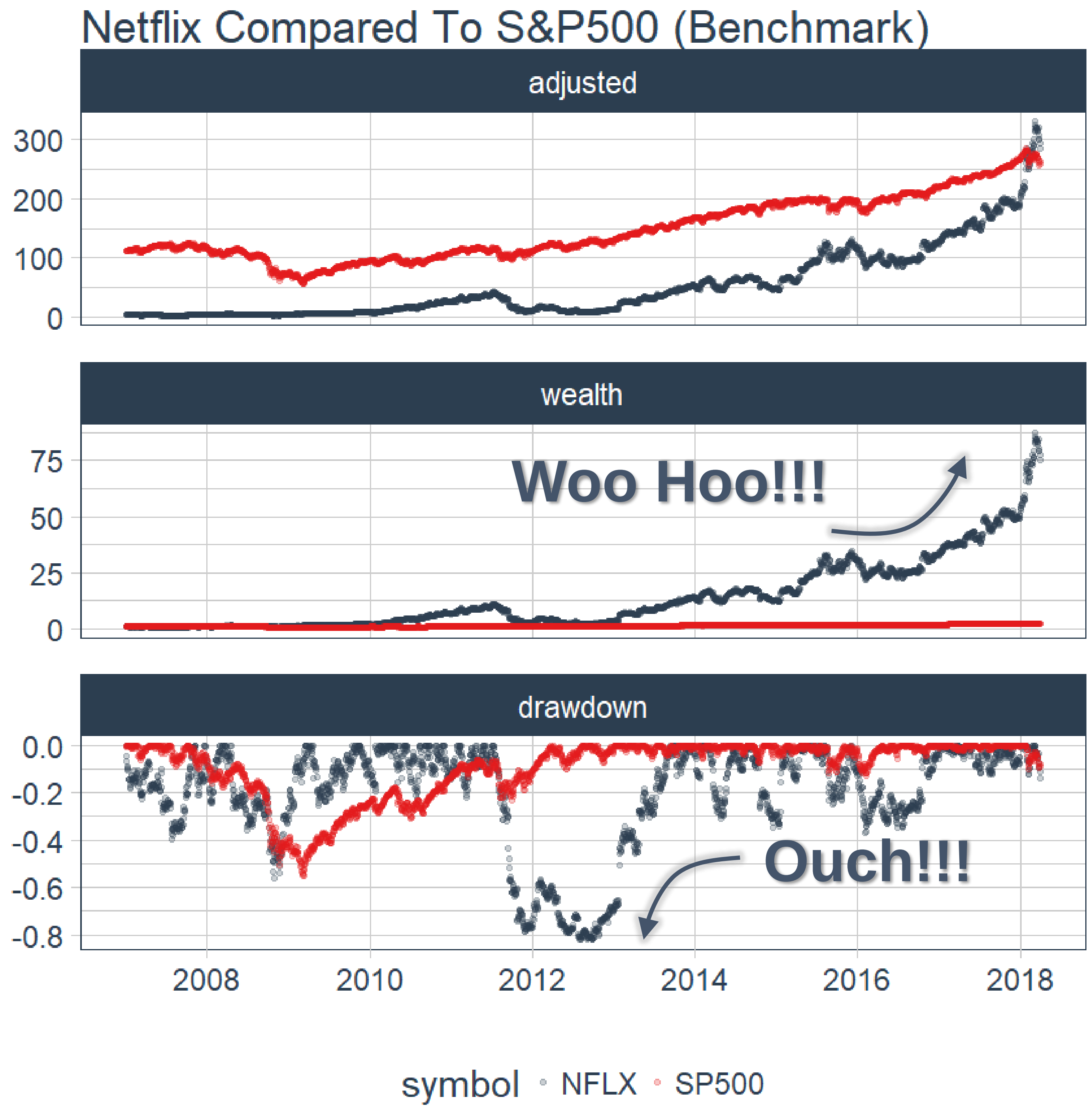
- Importance of Time Series
- Challenges & Opportunities
- Deep Learning for Time Series

Importance of Time Series

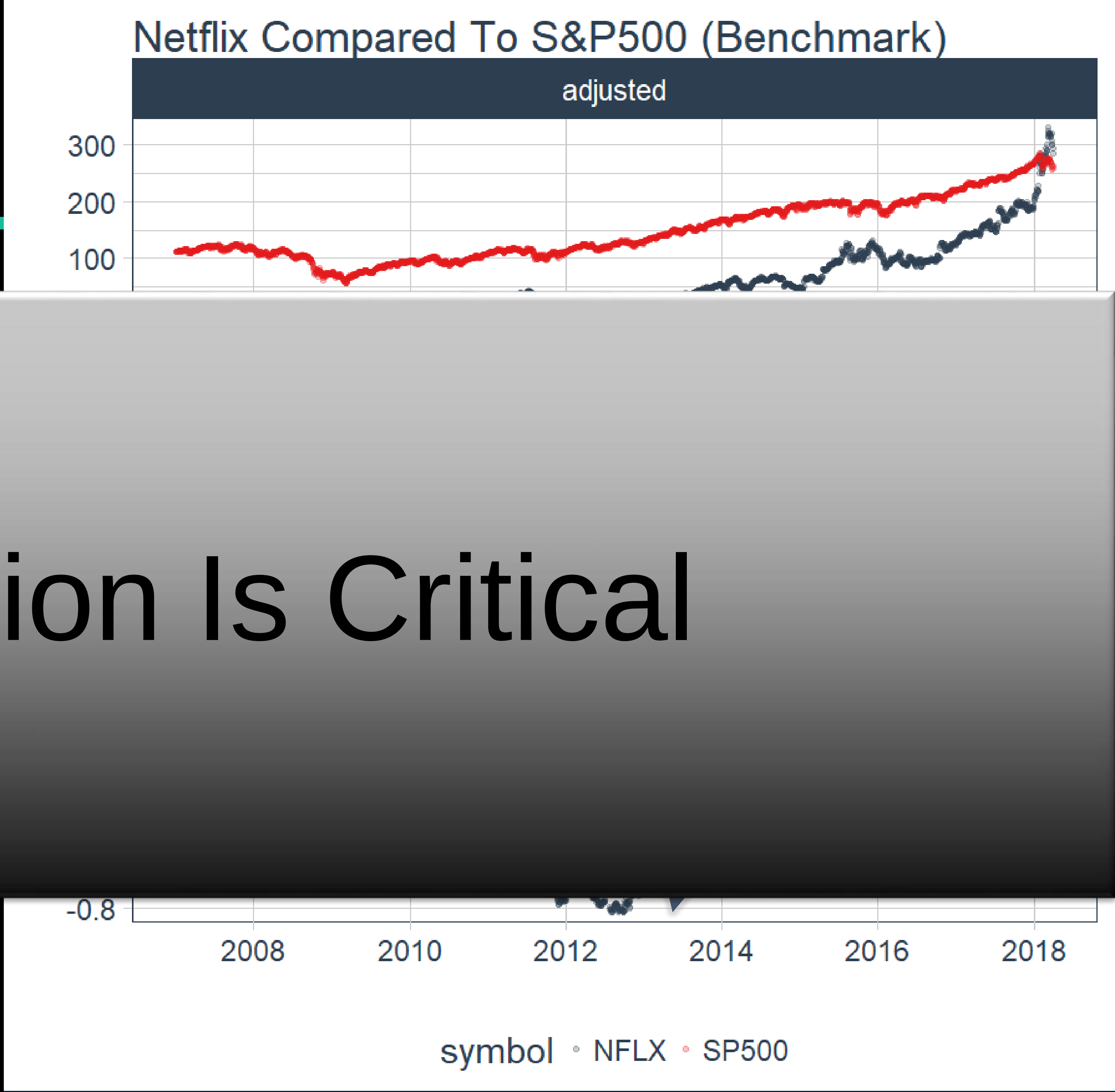
Importance of Time Series

Netflix vs S&P500

Gain vs Pain



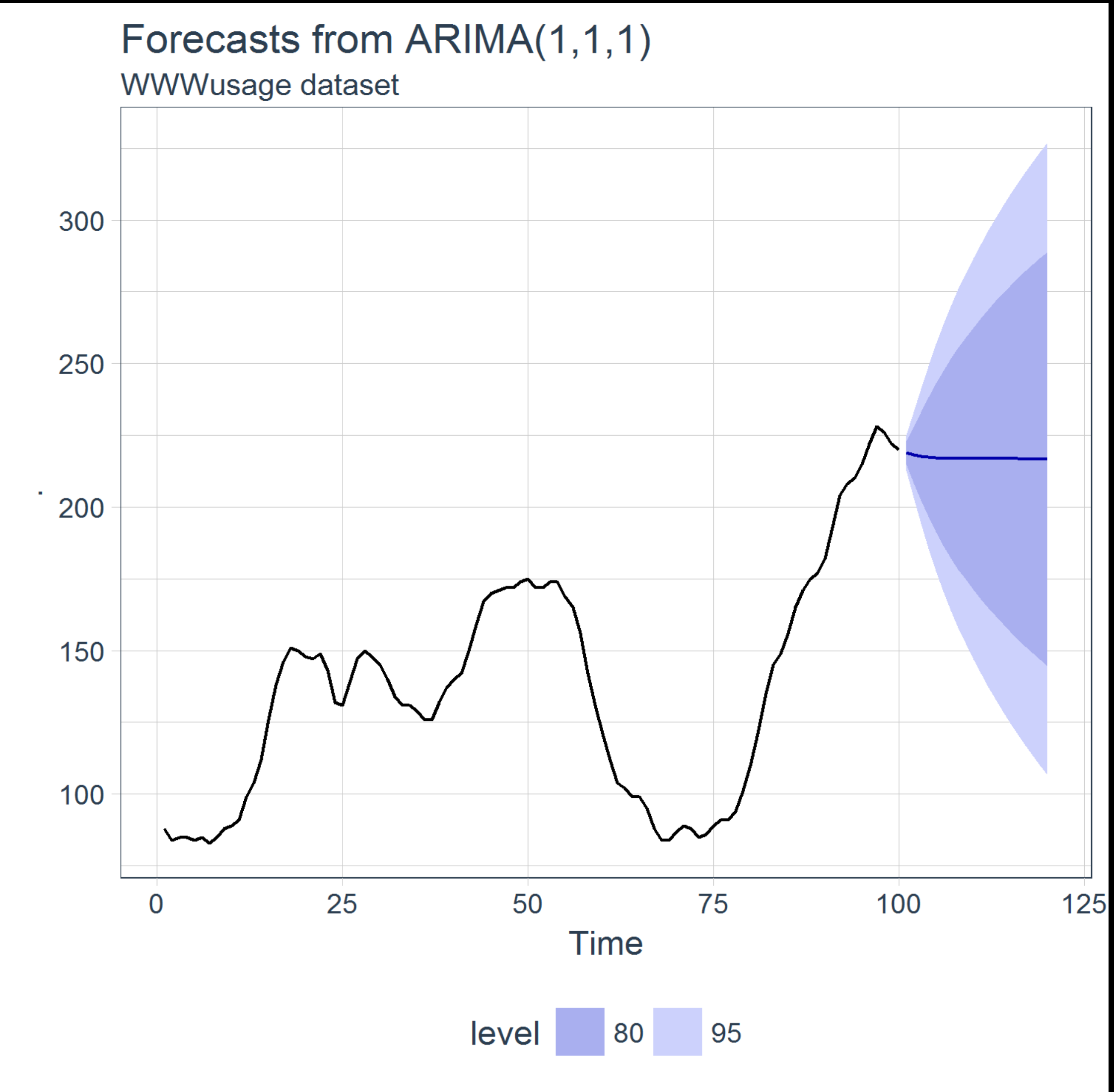
Importance of Time Series



Prediction Is Critical

New Challenges

Data Is Changing



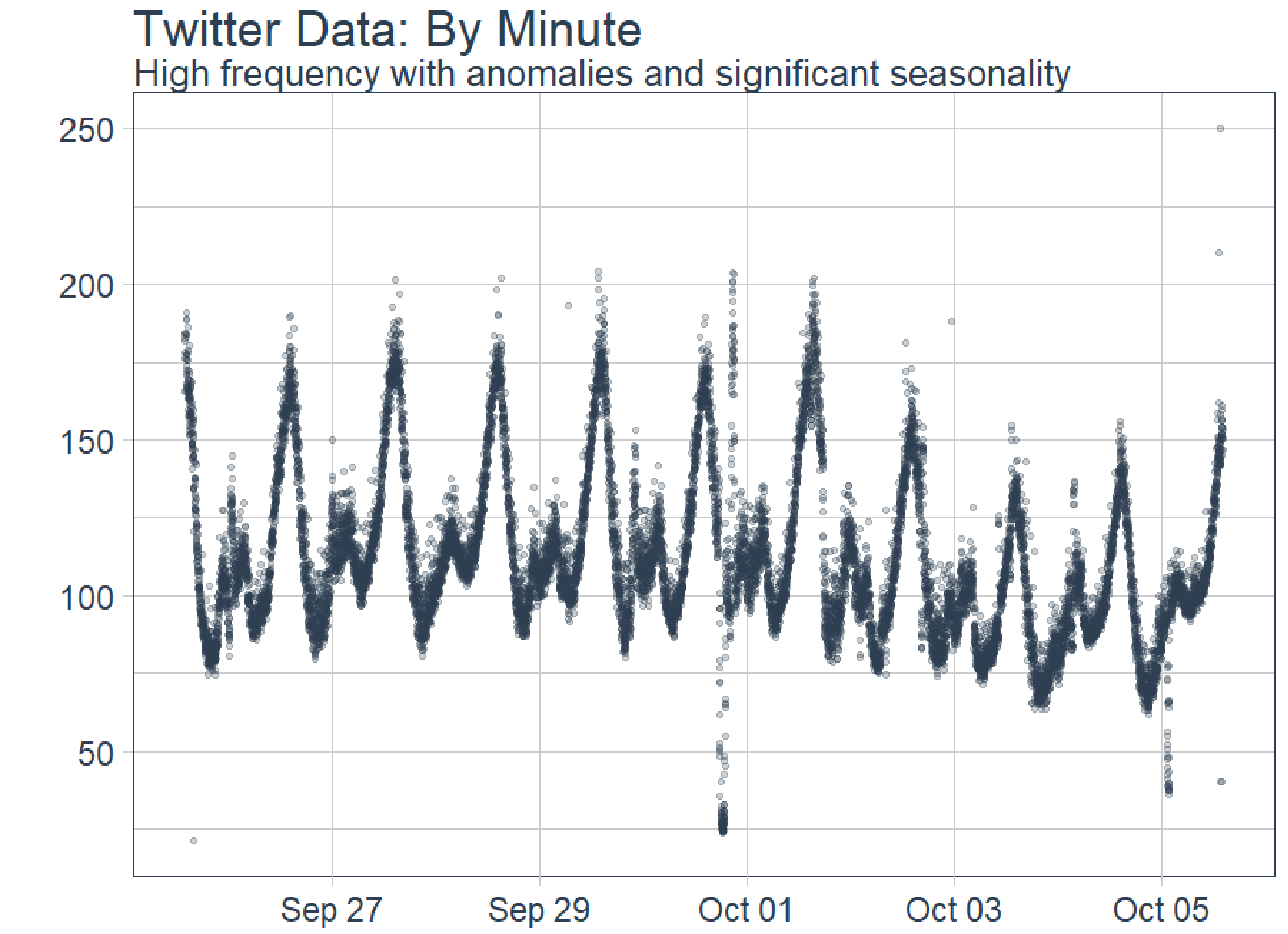
How Data Used to Be:

Short Time Series

Viewed As Univariate

Wide Forecast Margins

Today's Data Is Different



Source: https://github.com/twitter/AnomalyDetection

High Frequencies

Time-Based Pattern

Multivariate Systems

Sparse Data

Event Driven

Anomalies

New Opportunities For Time Series Prediction

New Techniques Available

- Machine Learning:
  - Time Series Signature Pattern Recognition

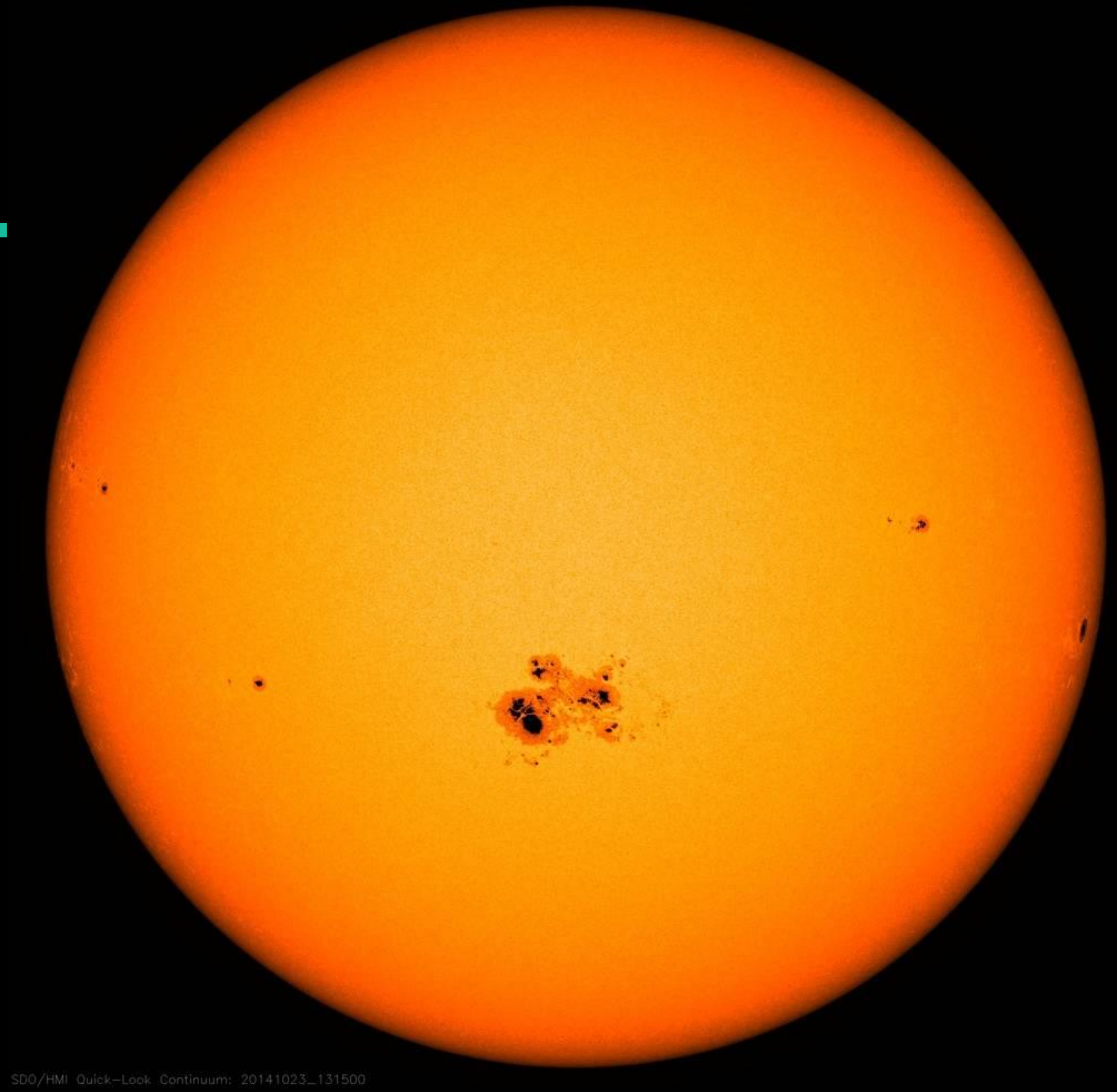
- Deep Learning:
  - Keras Stateful LSTMs

Our Focus Today

Deep Learning with
Keras Stateful LSTM

Sunspots Data

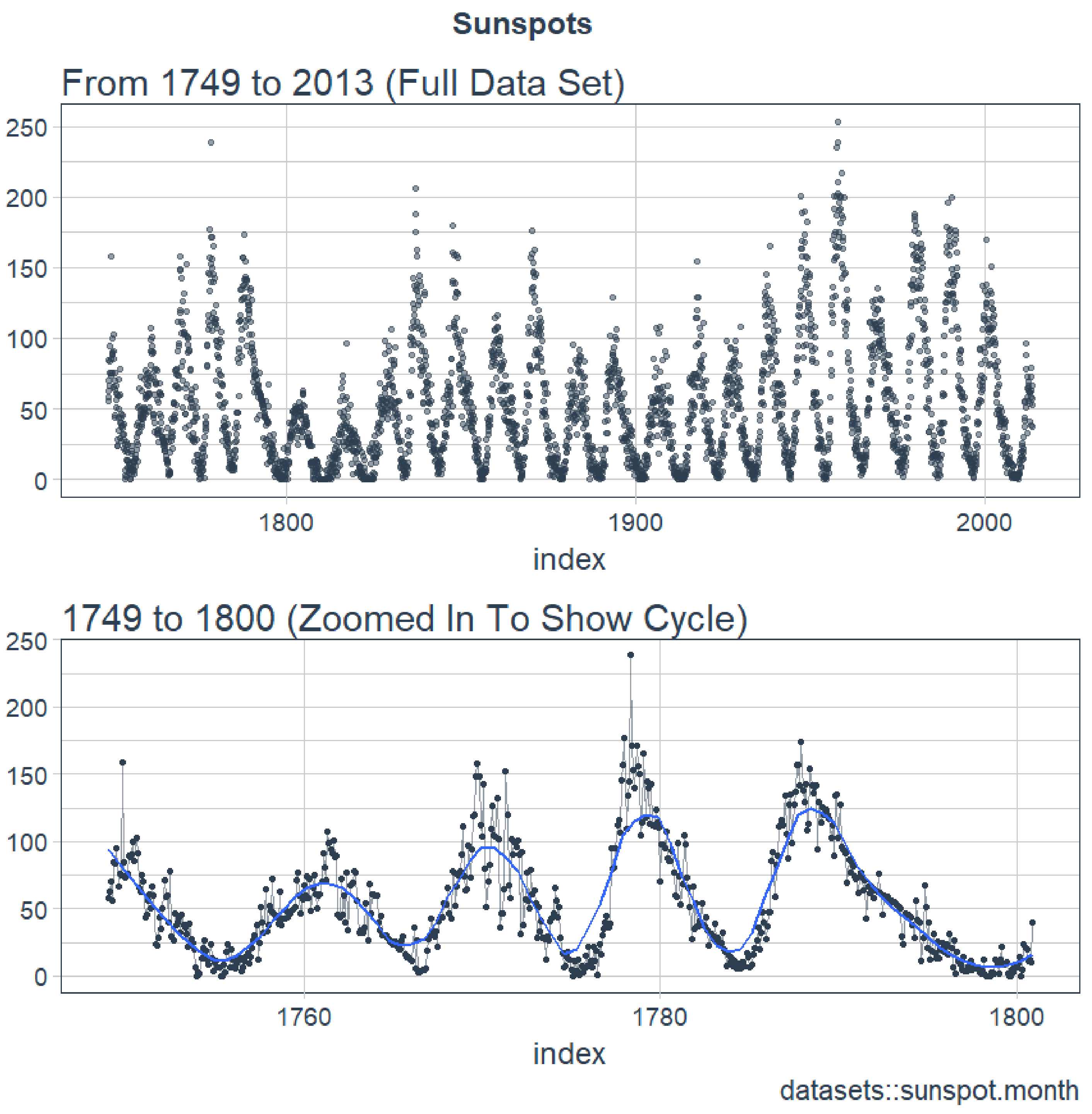
- Solar Phenomenon
- Great Example of ML Tool-Application Fit



Source: https://www.nasa.gov/content/goddard/largest-sunspot-of-solar-cycle

Sunspots Data

- Looks easy to predict
- Difficult
- Cycle & amplitude changes



Objective:

Predict

Next 10 Years

Using Keras Stateful LSTM

Learning Path

- What is an LSTM?
- Is LSTM a good candidate for the problem?
- Develop a Stateful LSTM Model using Keras
- Time Series Cross Validation using Backtesting

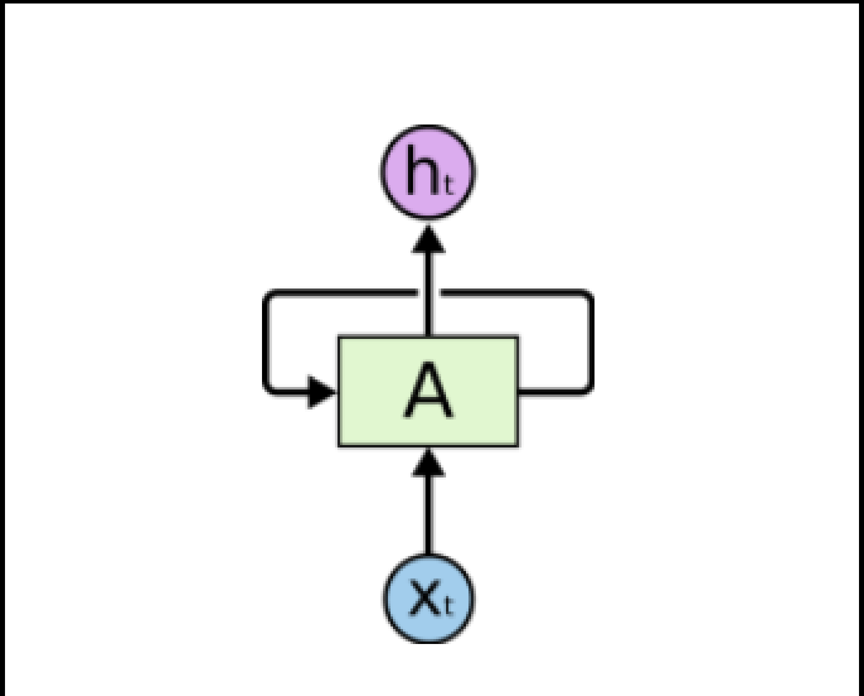
What is an LSTM?

- Special Type of Recurrent Neural Network (RNN)
- Long-Short Term Memory
- Models sequence data
- *"Understanding LSTM Networks"* by **Christopher Olah**

Source: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

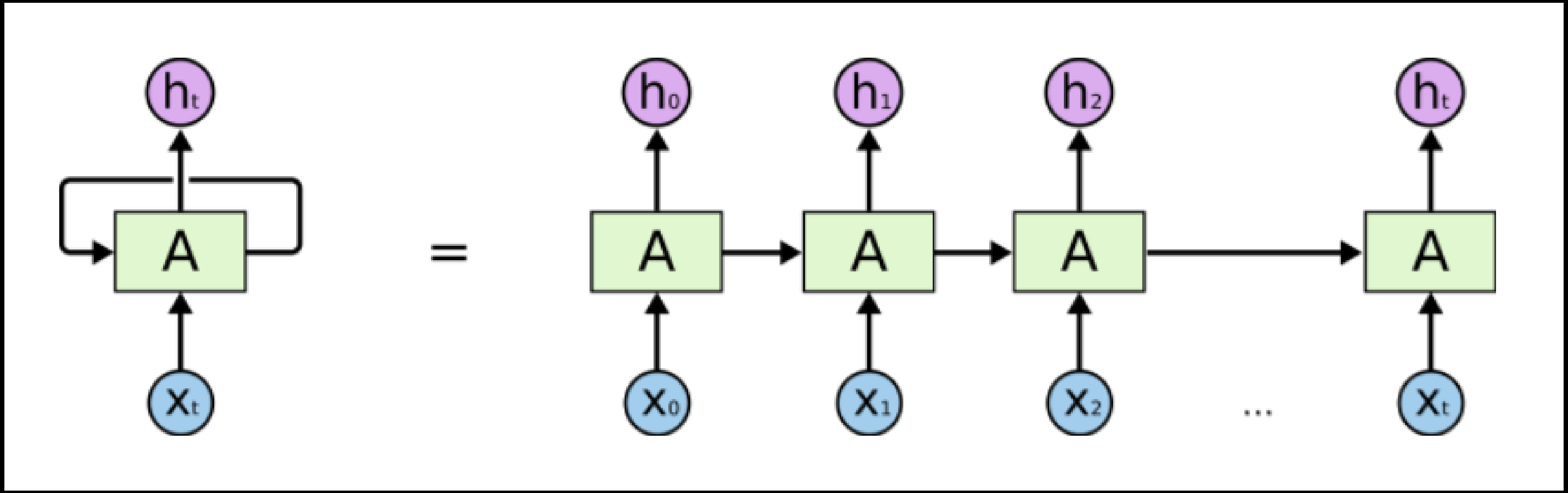
RNN

- RNNs have loops
- Enables persistence
- Strengths: Sequences
  - Learning context based on what happened previously
  - Speech recognition, image classifying, etc



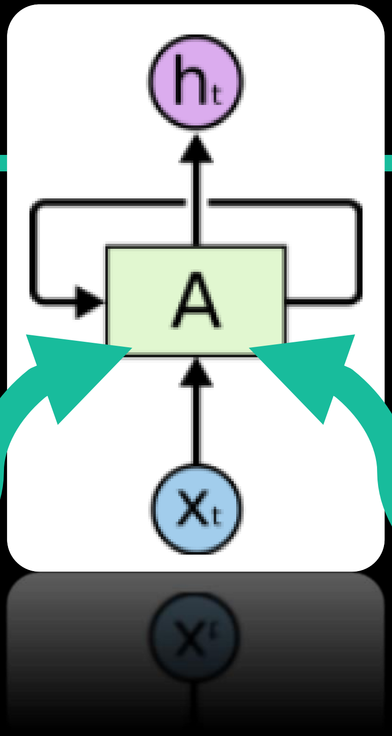
Source: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

Unrolling The RNN Loop

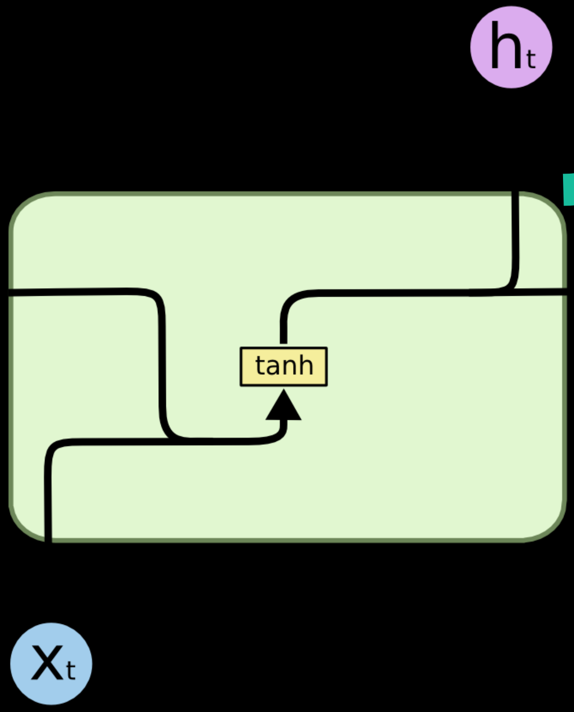


Source: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

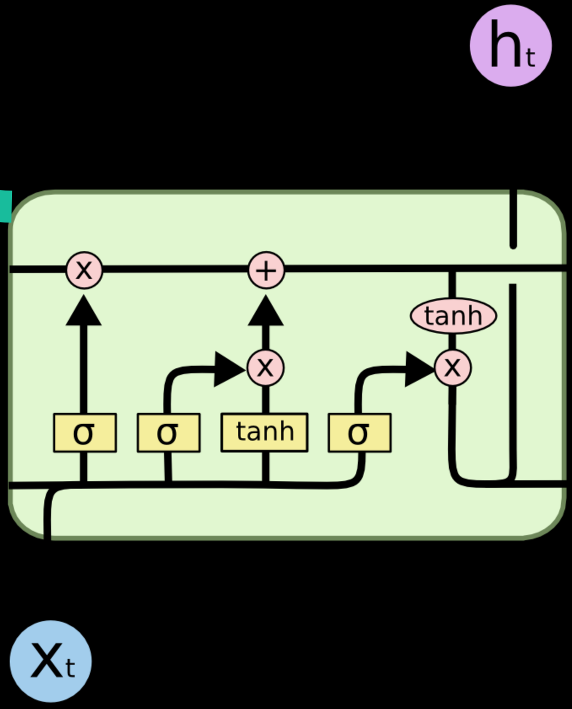
Inner Workings



RNN

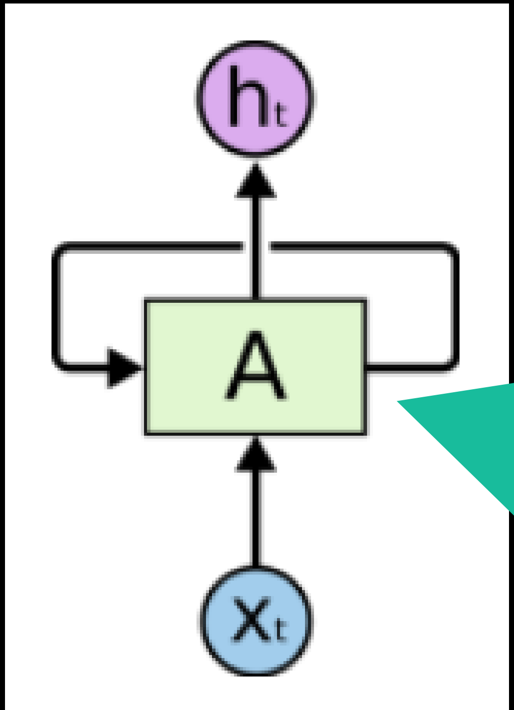


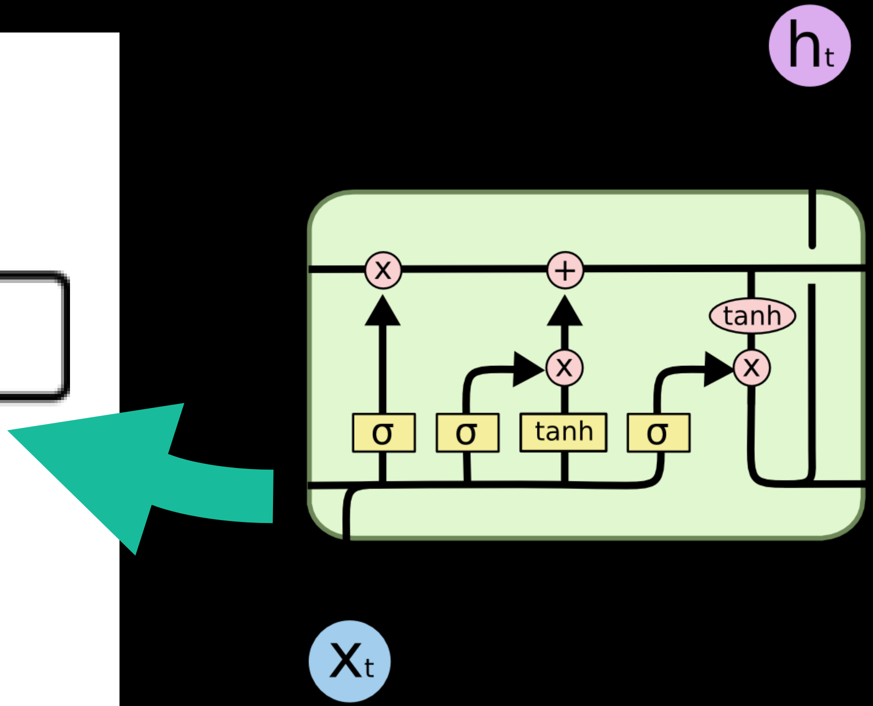
LSTM



Source: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

LSTM





Internal Cell Complexity Solves problem with basic RNNs:

Long Term Dependencies

Source: http://colah.github.io/posts/2015-08-Understanding-LSTMs/

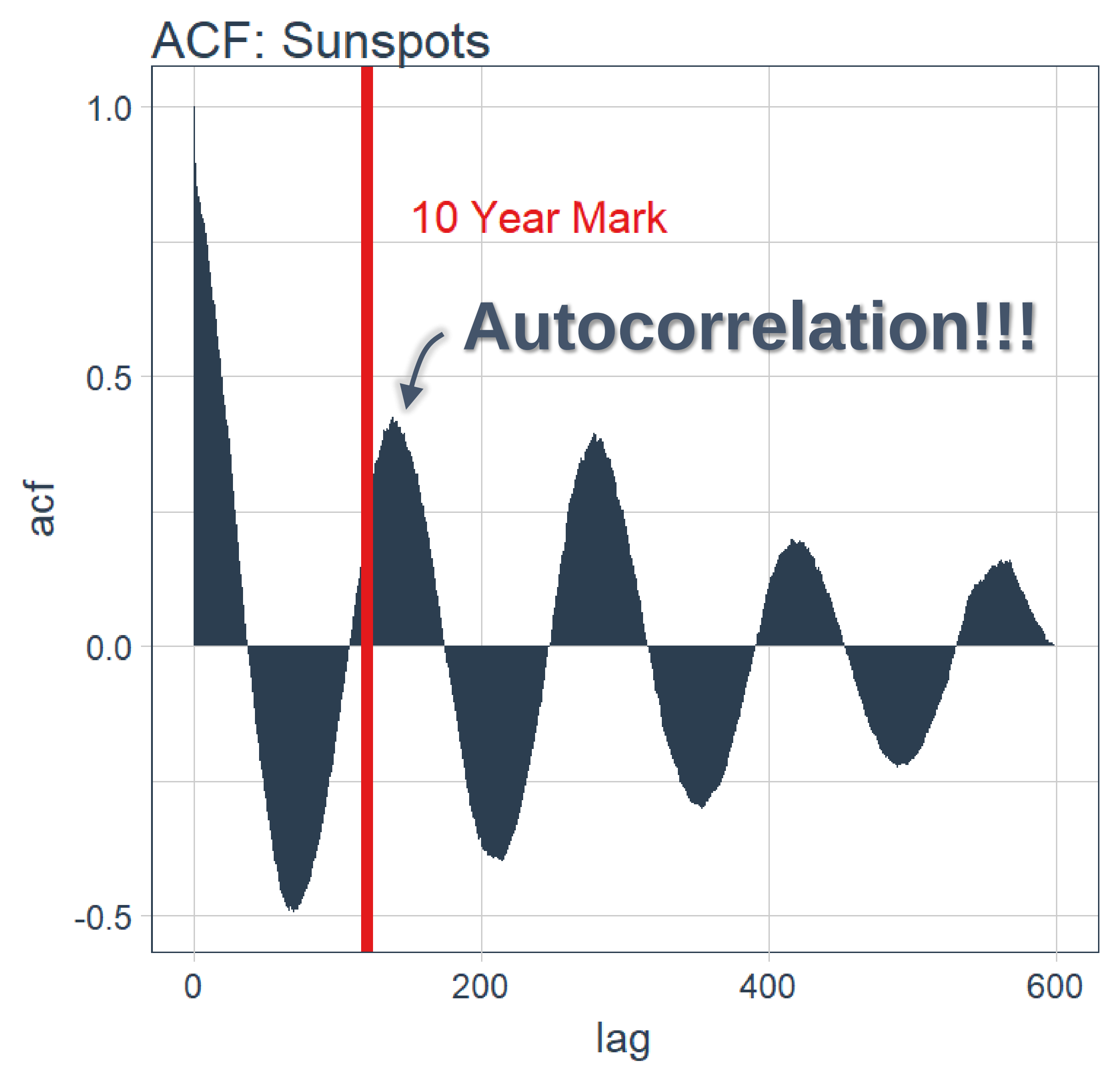
Is LSTM A Good Candidate?

Is LSTM A Good Candidate?

LSTM’s take advantage of autocorrelation

Is LSTM A Good Candidate?

- Autocorrelation
- Batch prediction
- Lag at 120 months (10 years) to predict next 10 years!
- LSTM is good candidate!



Developing A Stateful LSTM With Keras

Keras Stateful LSTM Terminology

- Batch Size:
  - The batch size is the number of training examples in one forward/backward pass of a RNN before a weight update
- Time Steps:
  - A time step is the number of lags included in the training/testing set
- Epochs:
  - The epochs are the total number of forward/backward pass iterations

Keras Input Setup

```
# setup inputs
lag_setting  <- 120 # = nrow(df_tst)
batch_size   <- 40
train_length <- 440
tsteps       <- 1
epochs       <- 300
```

Keras Stateful Model Setup

- Stateful: No reshuffling between batches
- Time dependency is preserved
- Higher accuracy than stateless

Modeling With Keras

Keras Stateful LSTM

```r
model <- keras_model_sequential()

model %>%
    layer_lstm(units            = 50,
               input_shape      = c(tsteps, 1),
               batch_size       = batch_size,
               return_sequences = TRUE,
               stateful         = TRUE) %>%
    layer_lstm(units            = 50,
               return_sequences = FALSE,
               stateful         = TRUE) %>%
    layer_dense(units = 1)

model %>%
    compile(loss = 'mae', optimizer = 'adam')

model
```

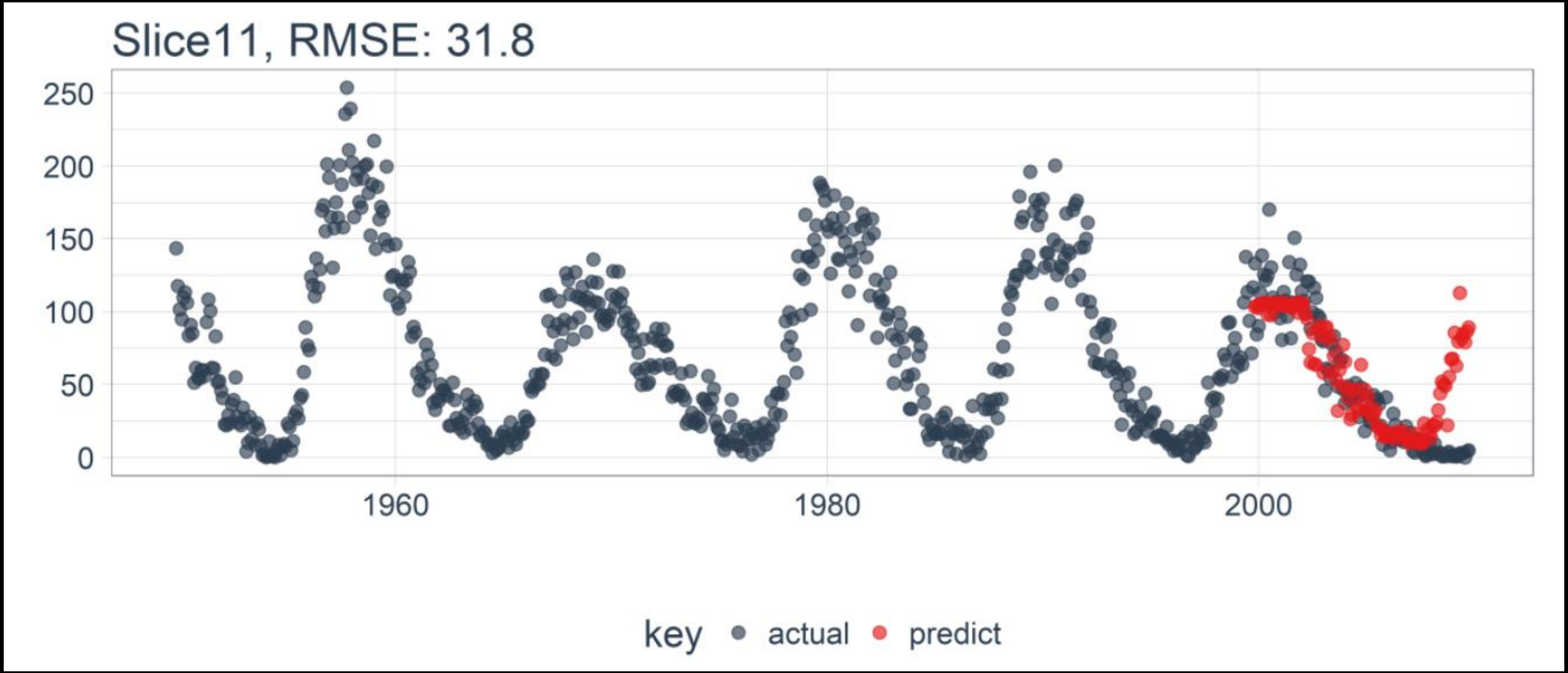

```
## Model
## ___________________________________________________________________________
## Layer (type)                     Output Shape                  Param #
## ===========================================================================
## lstm_1 (LSTM)                    (40, 1, 50)                   10400
## ___________________________________________________________________________
## lstm_2 (LSTM)                    (40, 50)                      20200
## ___________________________________________________________________________
## dense_1 (Dense)                  (40, 1)                       51
## ===========================================================================
## Total params: 30,651
## Trainable params: 30,651
## Non-trainable params: 0
## ___________________________________________________________________________
```

Keras Stateful LSTM

Fitting The Model

```
for (i in 1:epochs) {
    model %>% fit(x          = x_train_arr,
                  y          = y_train_arr,
                  batch_size = batch_size,
                  epochs     = 1,
                  verbose    = 1,
                  shuffle    = FALSE)

    model %>% reset_states()
    cat("Epoch: ", i)

}
```

Keras Stateful LSTM



Backtesting

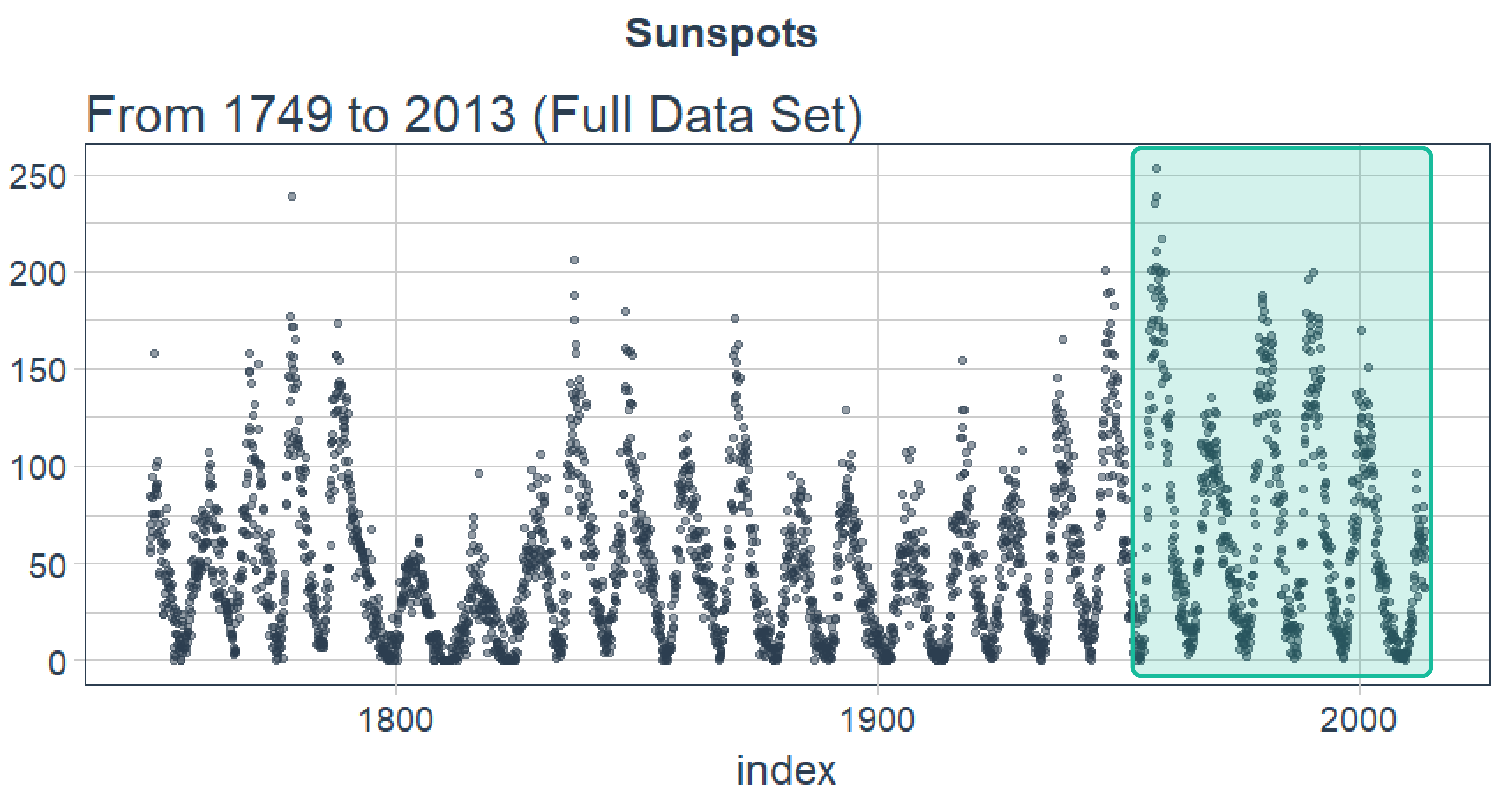
Backtesting Strategy

rsample::rolling_origin()

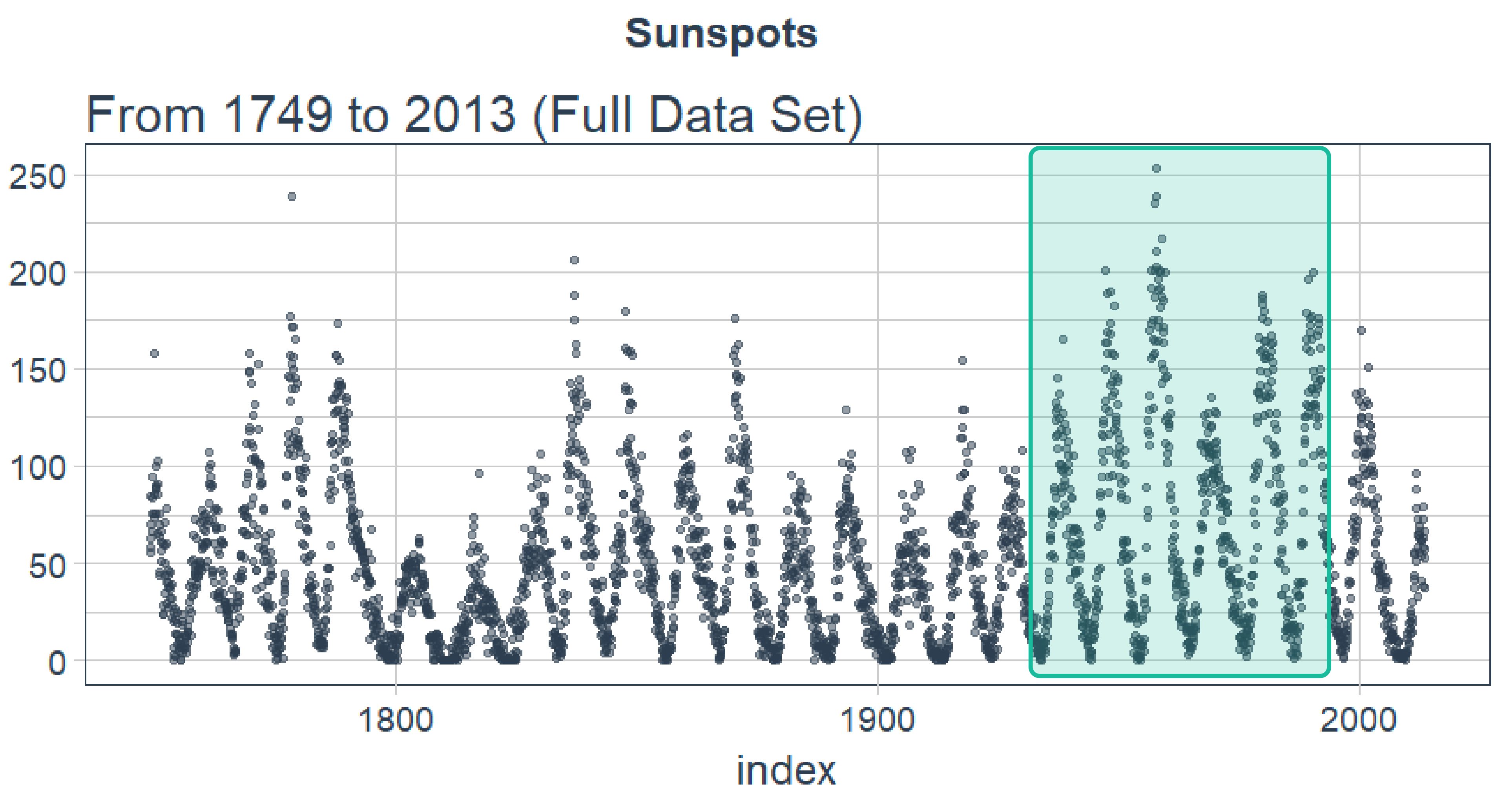
```
periods_train <- 12 * 50
periods_test  <- 12 * 10
skip_span     <- 12 * 20

rolling_origin_resamples <- rolling_origin(
    sun_spots,
    initial    = periods_train,
    assess     = periods_test,
    cumulative = FALSE,
    skip       = skip_span
)

rolling_origin_resamples
```

```
## # Rolling origin forecast resampling
## # A tibble: 11 x 2
##    splits         id
##    <list>         <chr>
##  1 <S3: rsplit> Slice01
##  2 <S3: rsplit> Slice02
##  3 <S3: rsplit> Slice03
##  4 <S3: rsplit> Slice04
##  5 <S3: rsplit> Slice05
##  6 <S3: rsplit> Slice06
##  7 <S3: rsplit> Slice07
##  8 <S3: rsplit> Slice08
##  9 <S3: rsplit> Slice09
## 10 <S3: rsplit> Slice10
## 11 <S3: rsplit> Slice11
```

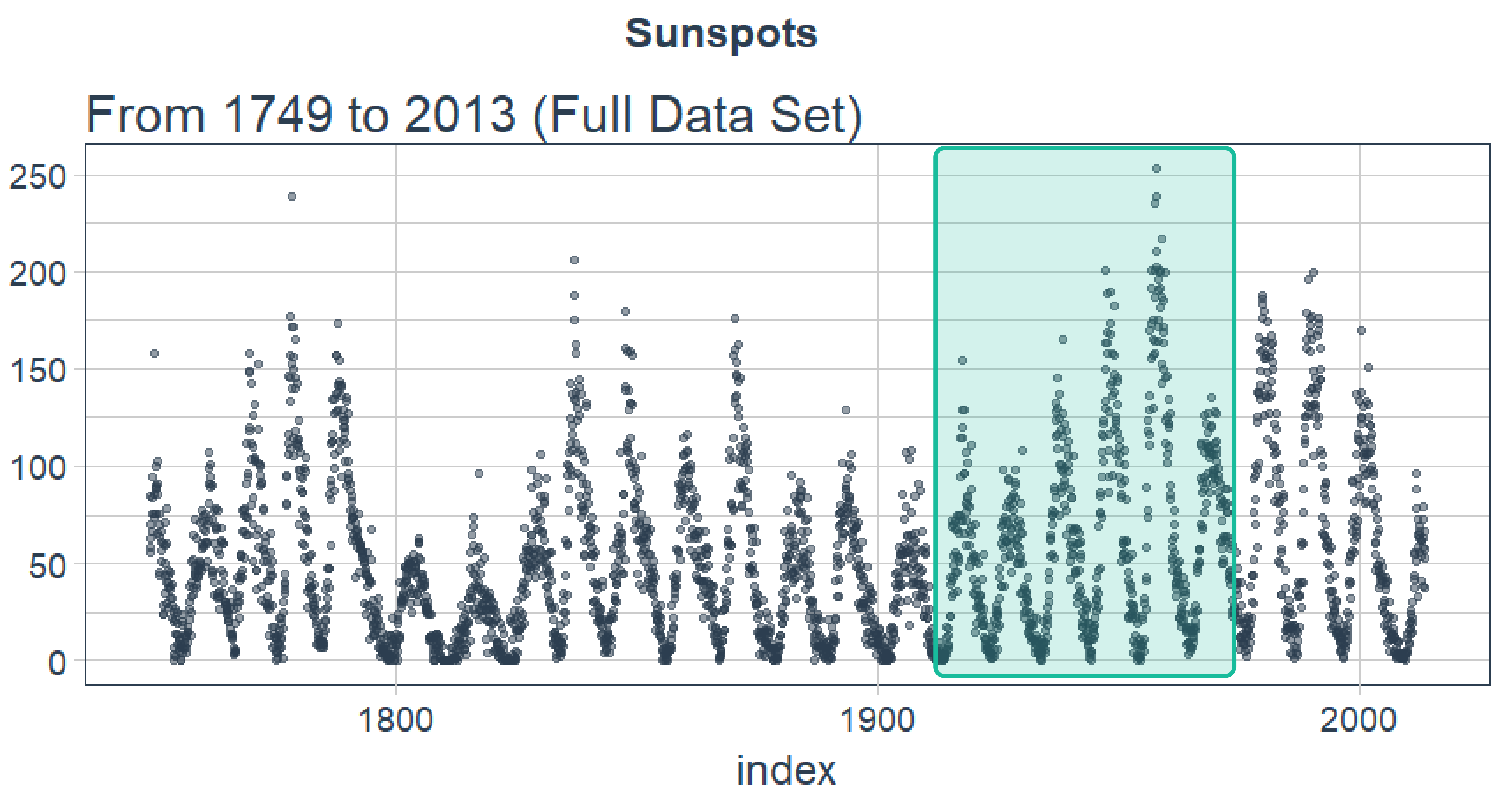
rsample::rolling_origin()



rsample::rolling_origin()



rsample::rolling_origin()



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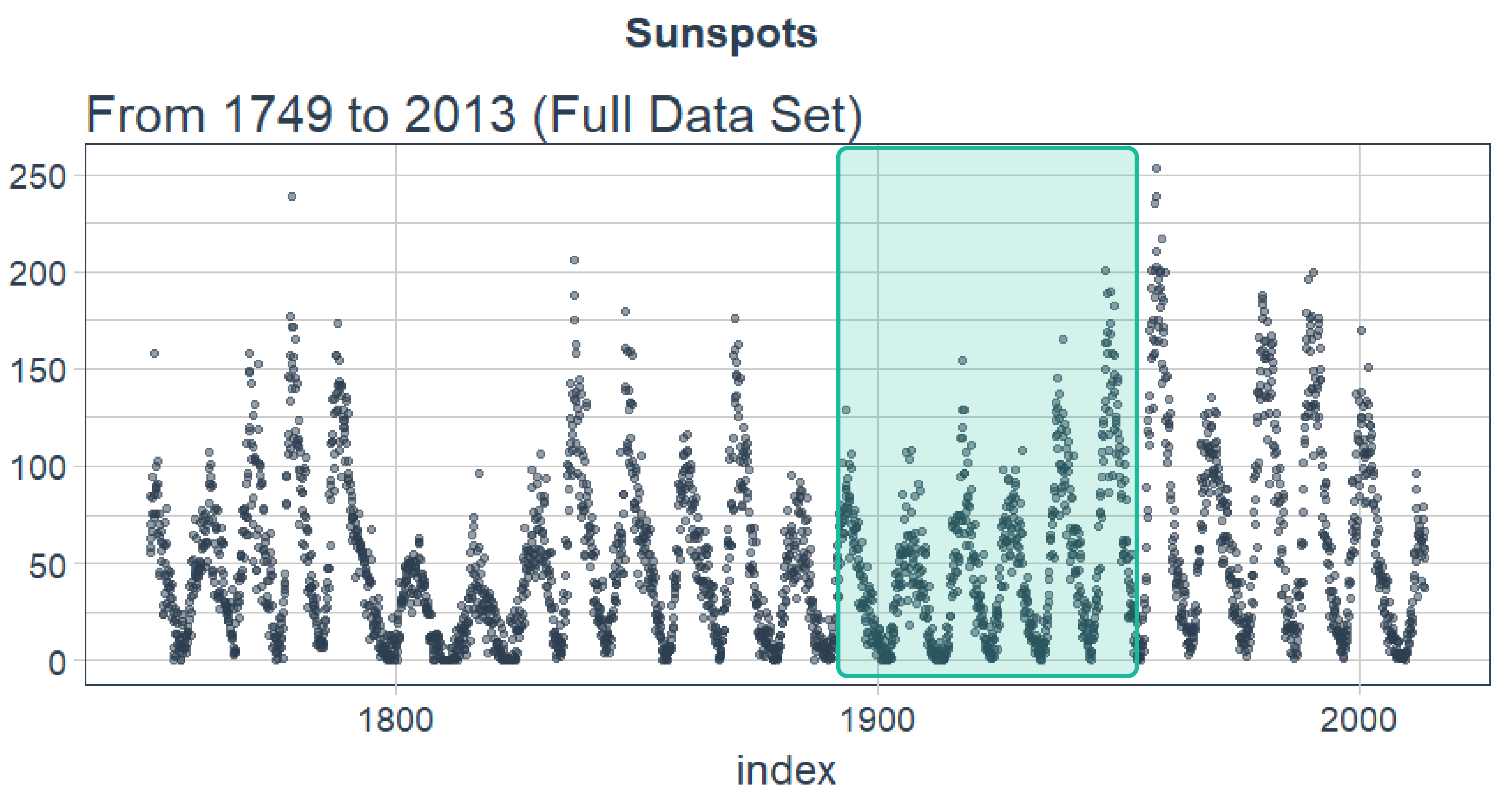

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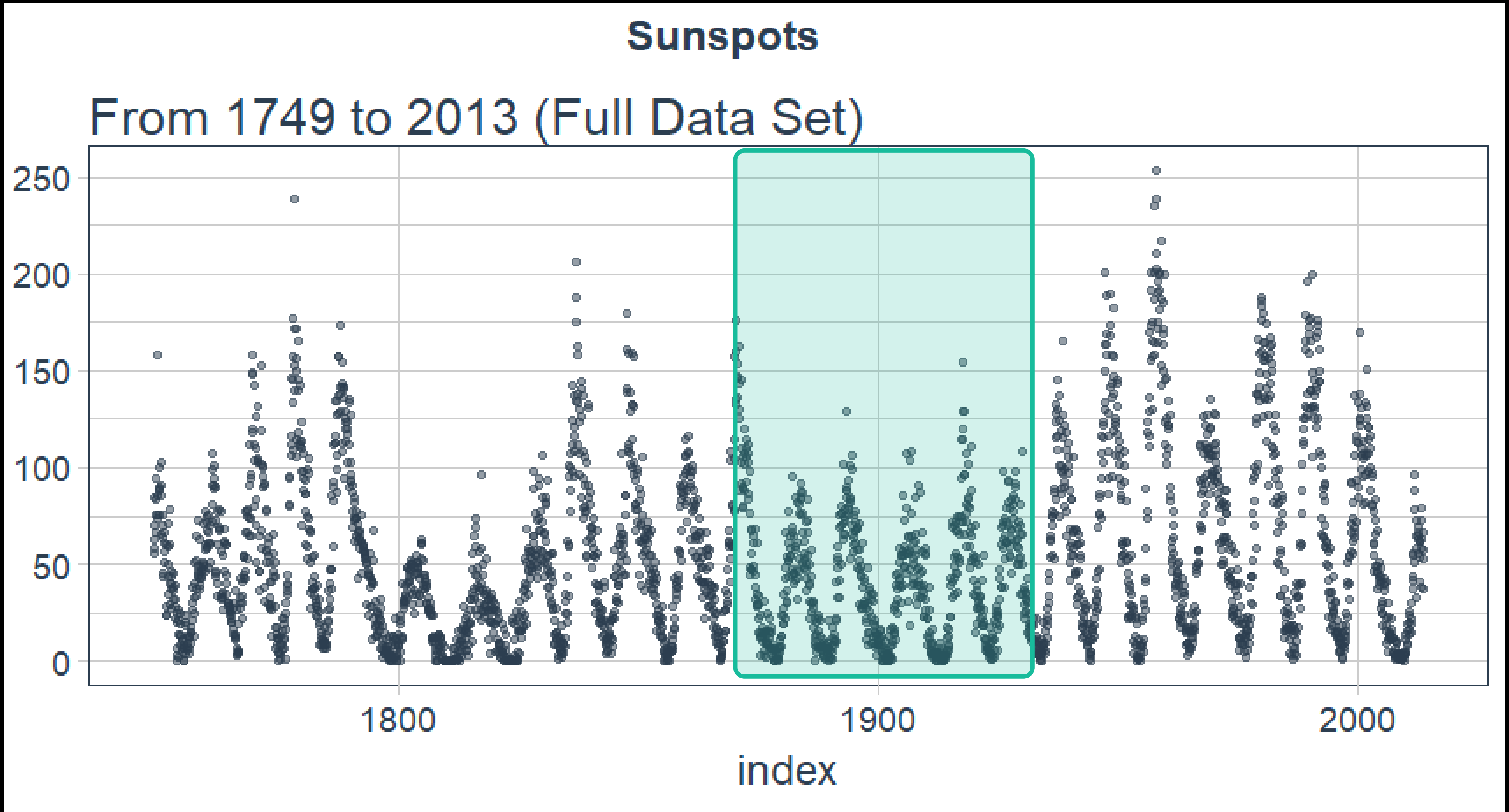

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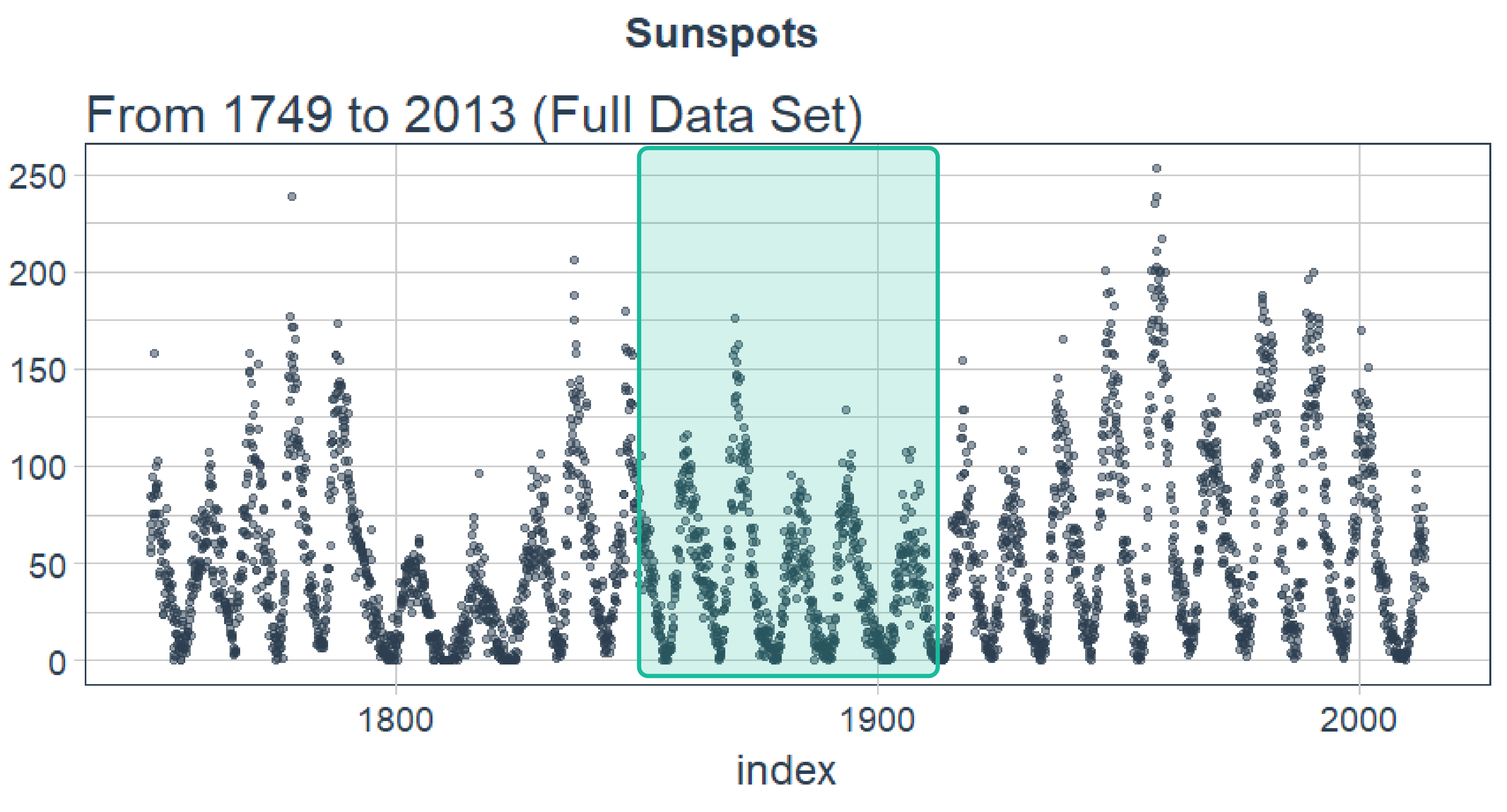

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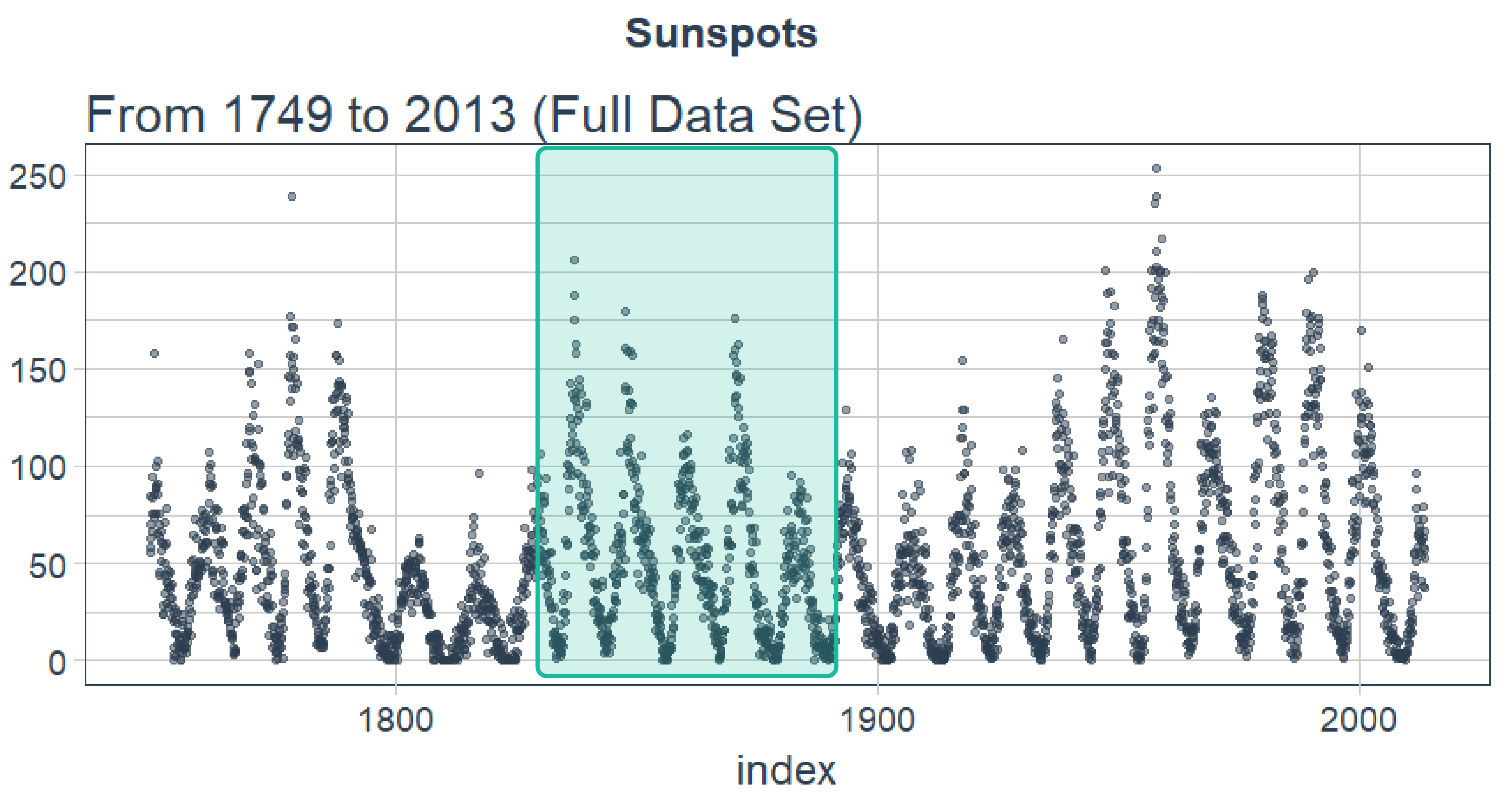
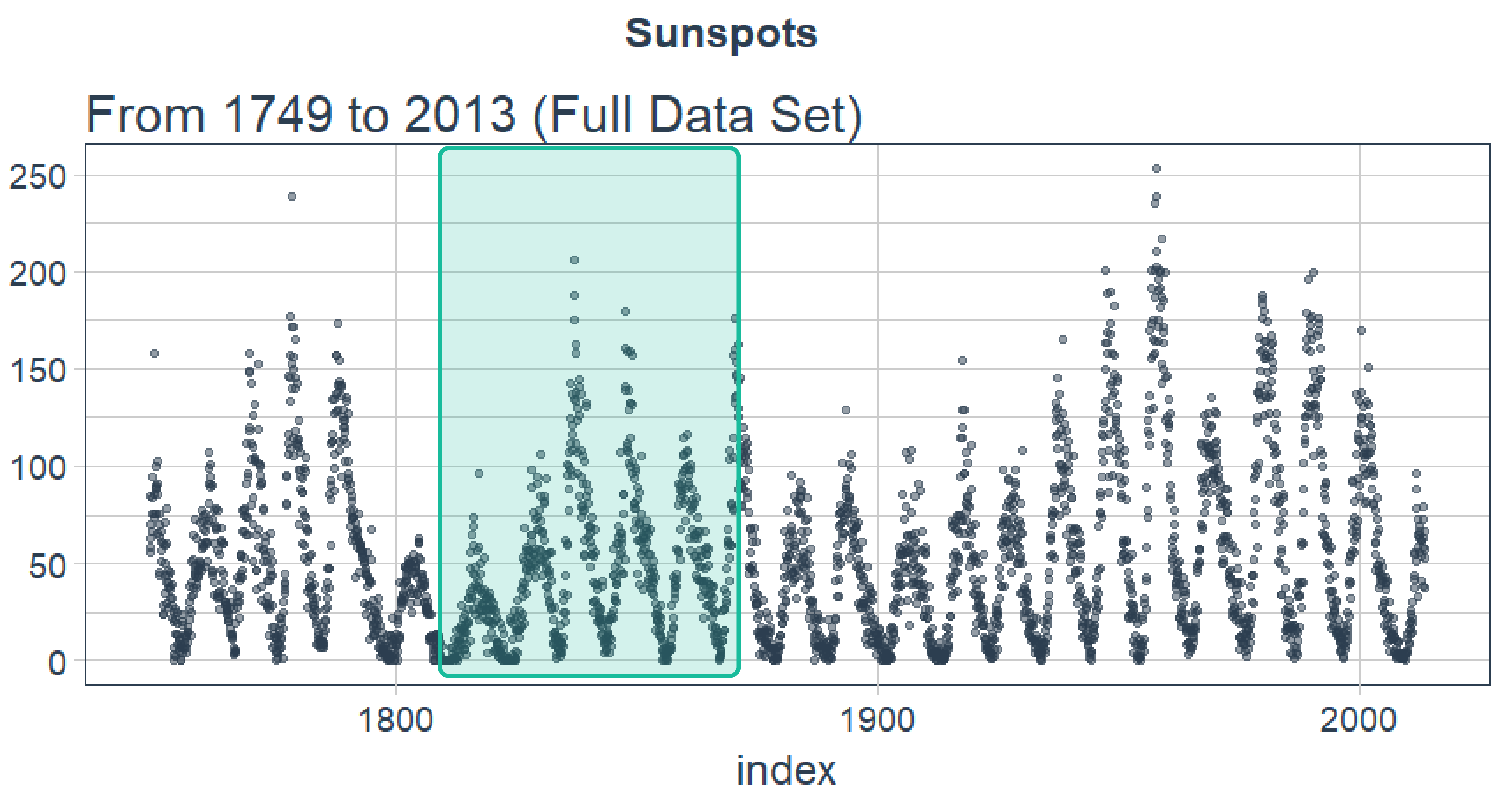
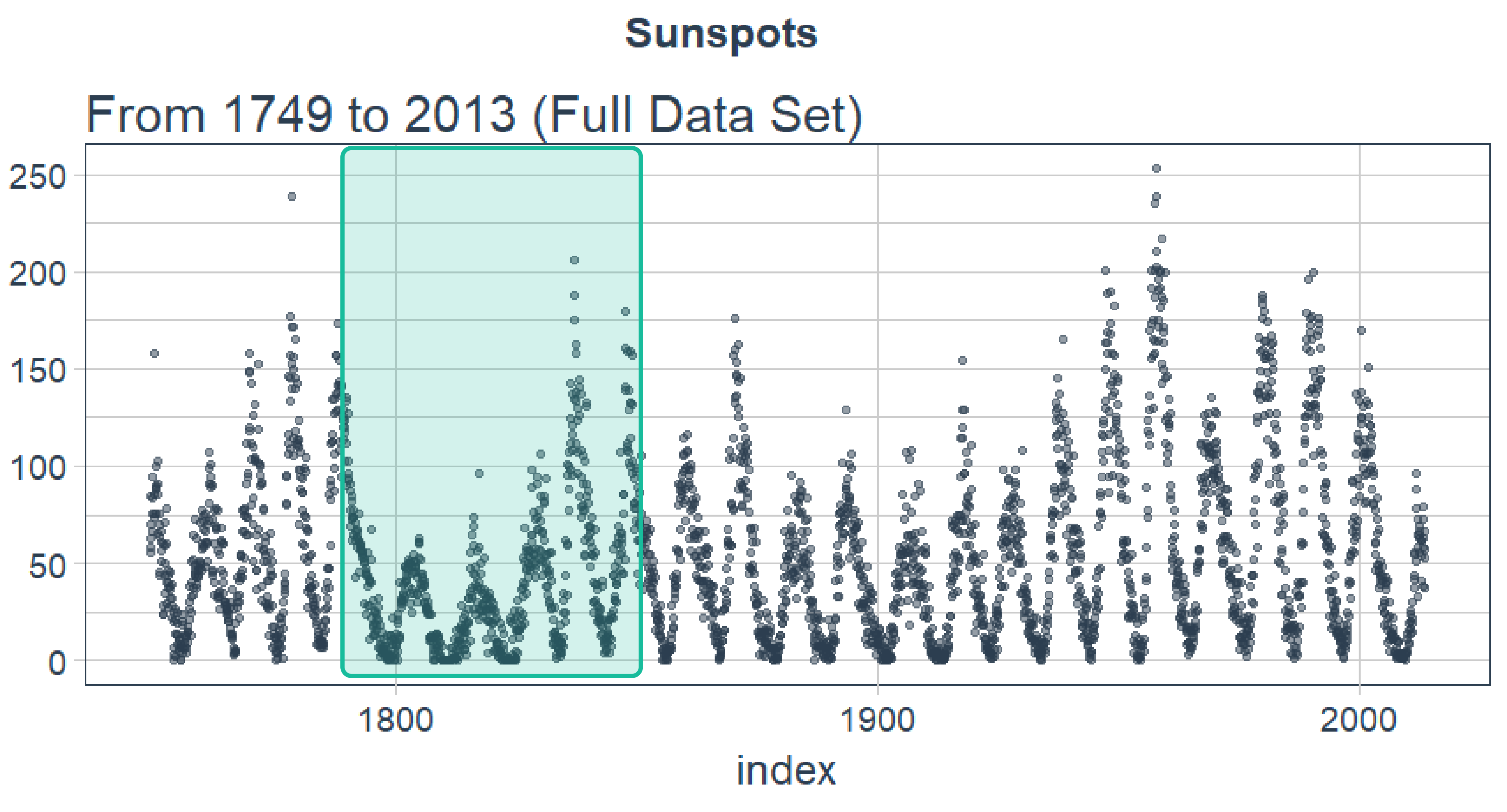


rsample::rolling_origin()



rsample::rolling_origin()



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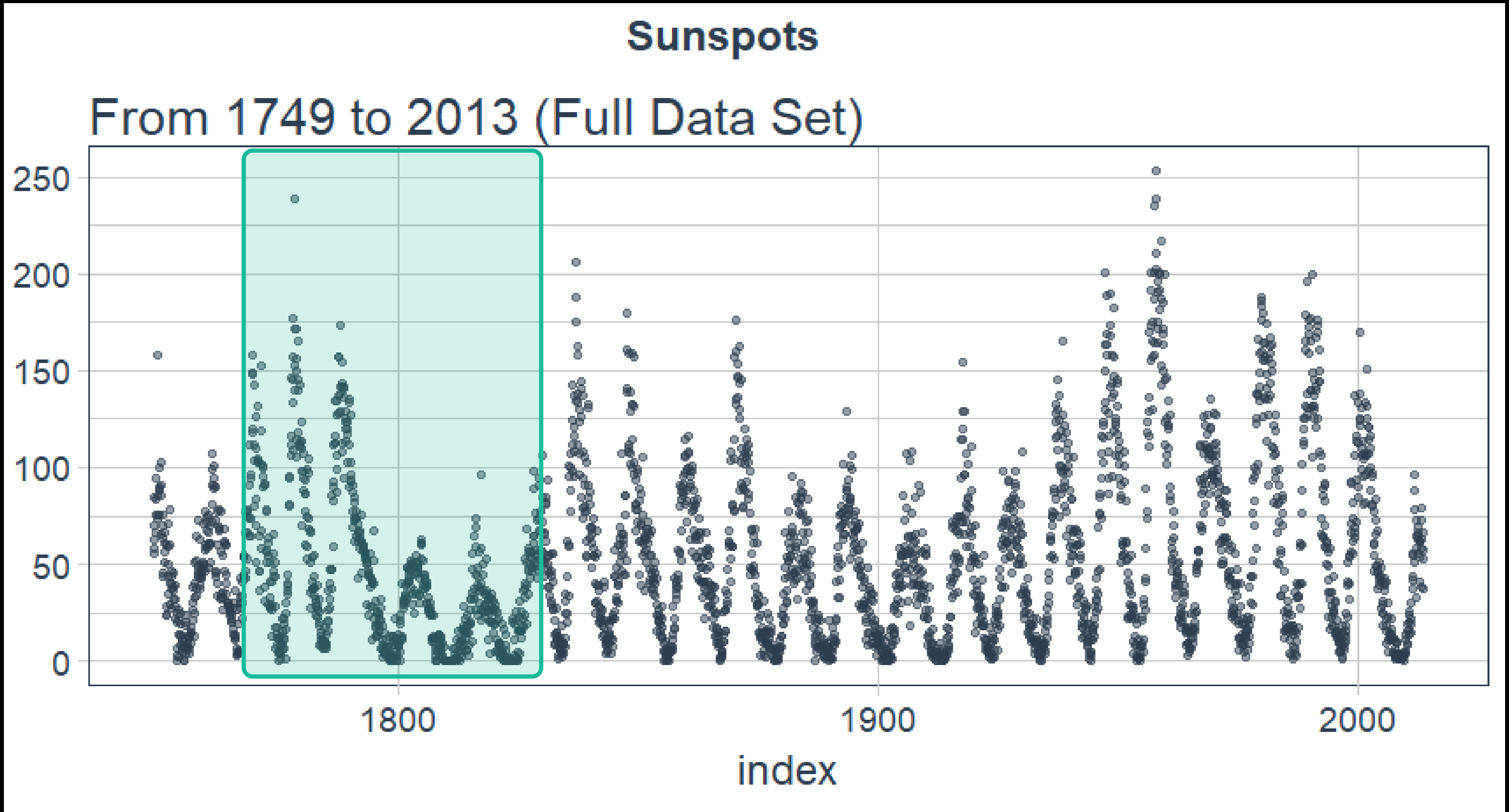
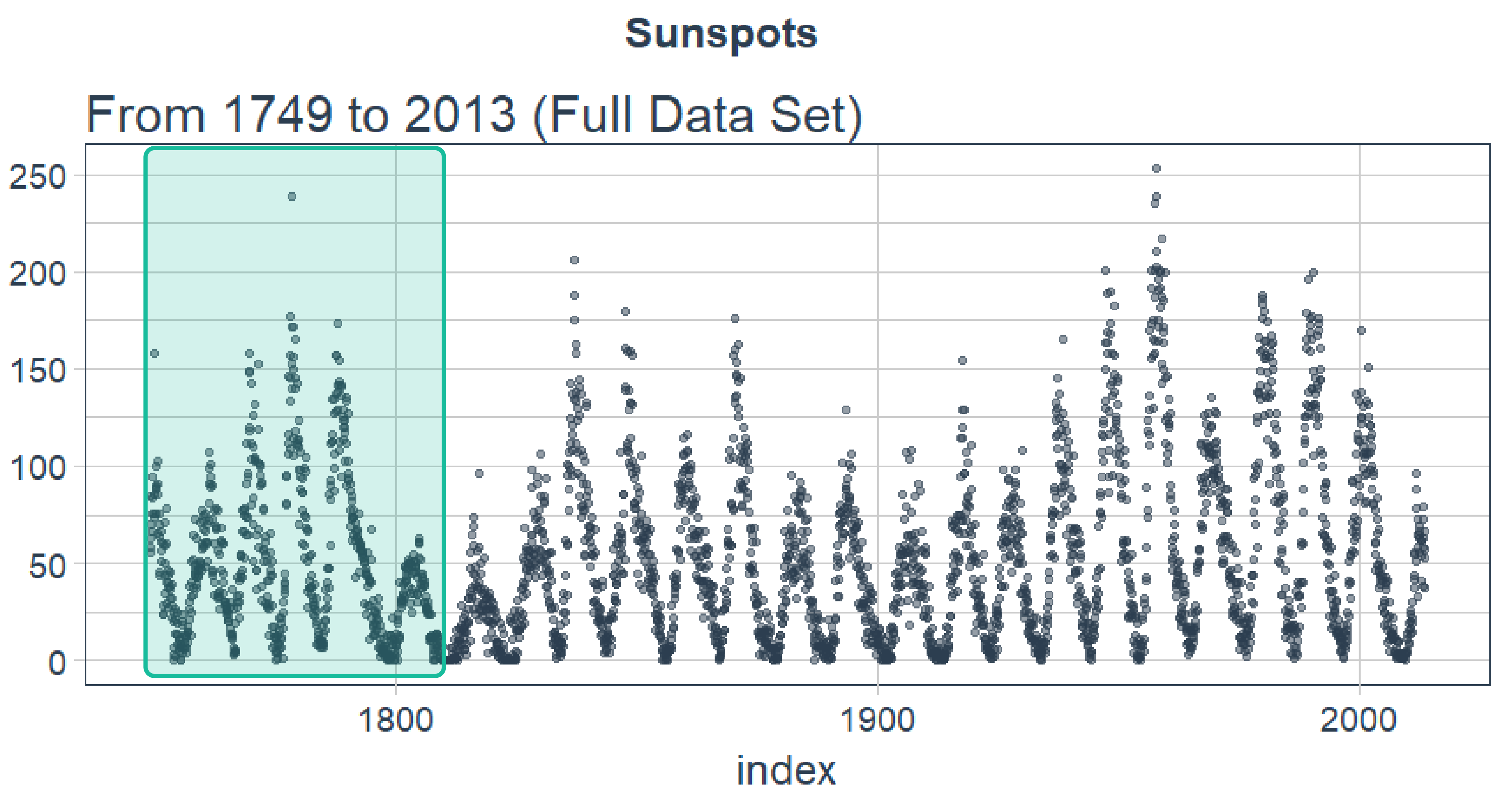
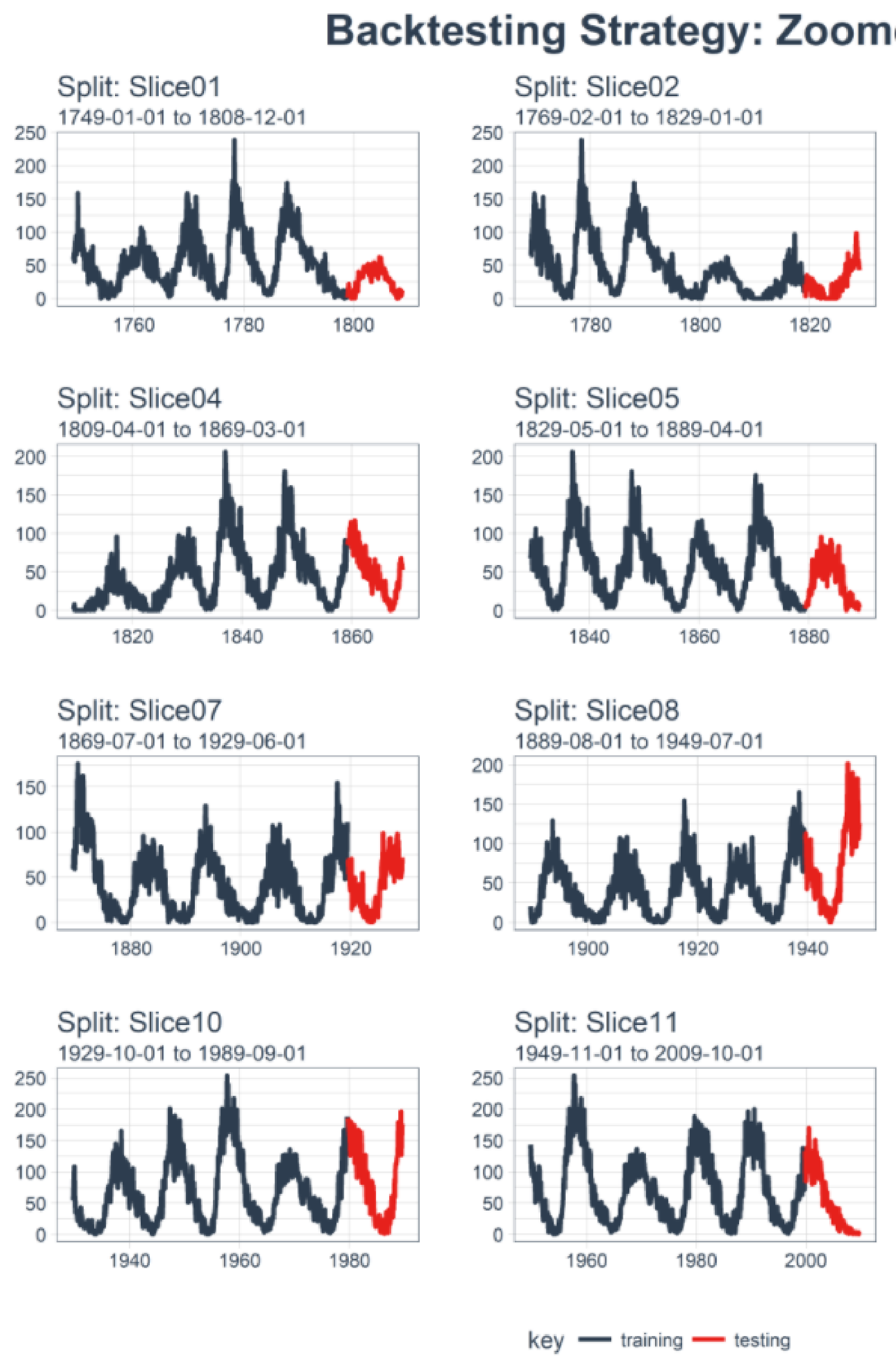


rsample::rolling_origin()



Backtesting Strategy

- rolling_origin()
- 1 Time Series
- 11 Samples →

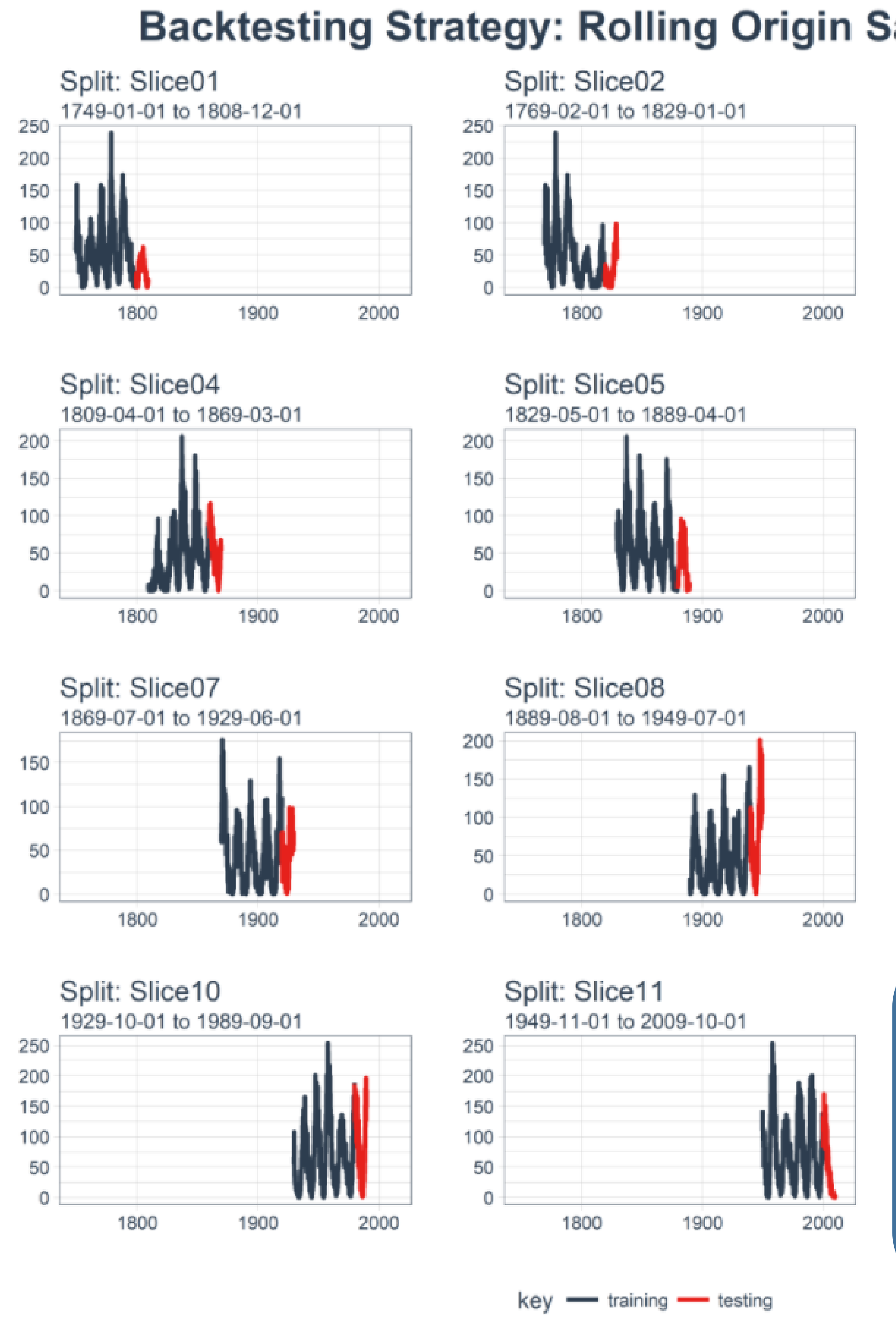


Key:
Training
Testing

Backtesting Strategy

Zoomed Out

Train: 50 years
Test: 10 years
Gap: 20 years



Key:
Training
Testing

Results

Keras LSTM Results

map(): custom keras prediction function

```
sample_predictions_lstm_tbl <- rolling_origin_resamples %>%
    mutate(predict = map(splits, predict_keras_lstm, epochs = 300))
```

Keras LSTM Results

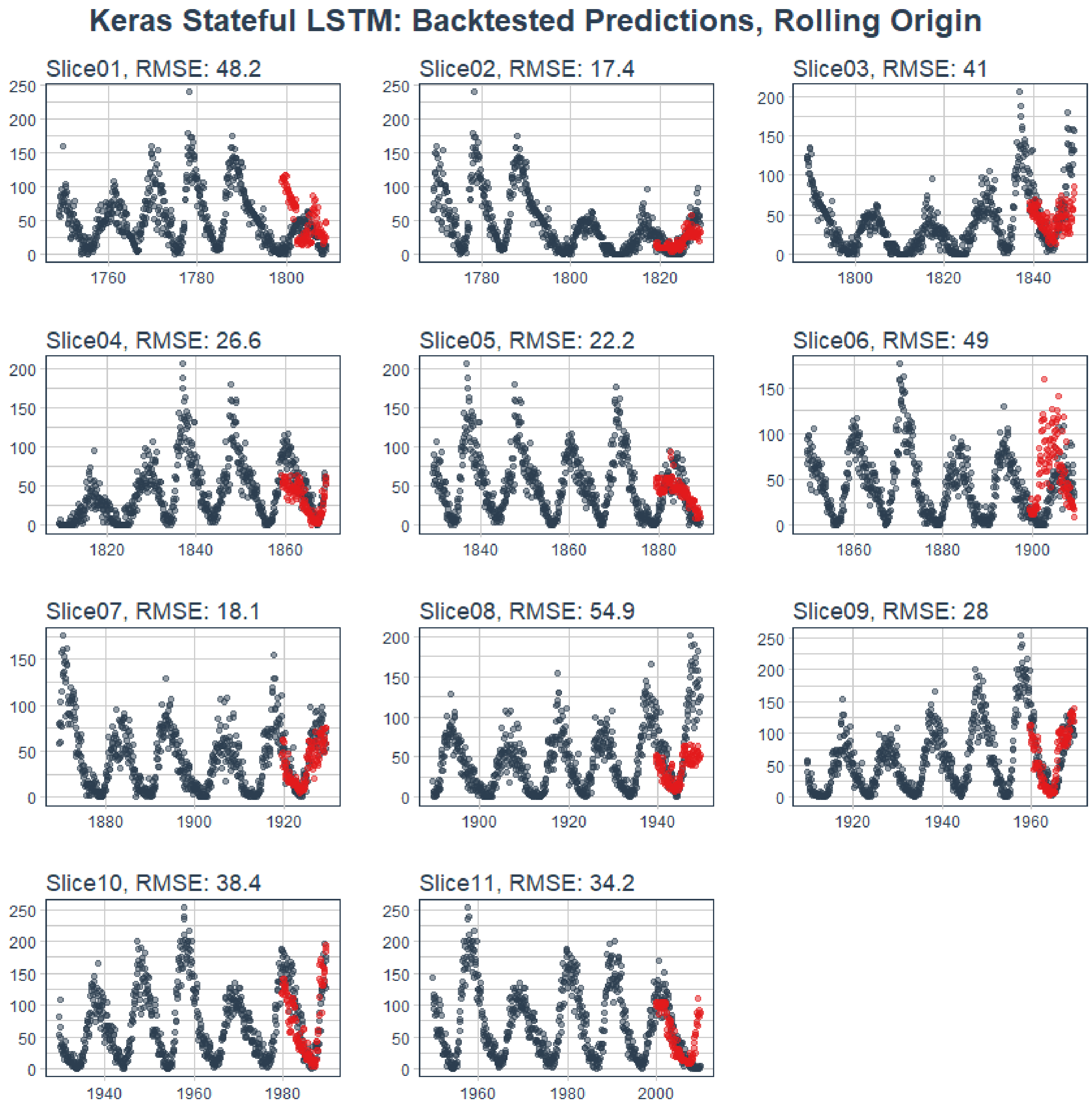
map(): custom keras prediction function

```
## # Rolling origin forecast resampling
## # A tibble: 11 x 3
##    splits         id      predict
##  * <list>         <chr>   <list>
##  1 <S3: rsplit> Slice01 <tibble [840 x 3]>
##  2 <S3: rsplit> Slice02 <tibble [840 x 3]>
##  3 <S3: rsplit> Slice03 <tibble [840 x 3]>
##  4 <S3: rsplit> Slice04 <tibble [840 x 3]>
##  5 <S3: rsplit> Slice05 <tibble [840 x 3]>
##  6 <S3: rsplit> Slice06 <tibble [840 x 3]>
##  7 <S3: rsplit> Slice07 <tibble [840 x 3]>
##  8 <S3: rsplit> Slice08 <tibble [840 x 3]>
##  9 <S3: rsplit> Slice09 <tibble [840 x 3]>
## 10 <S3: rsplit> Slice10 <tibble [840 x 3]>
## 11 <S3: rsplit> Slice11 <tibble [840 x 3]>
```

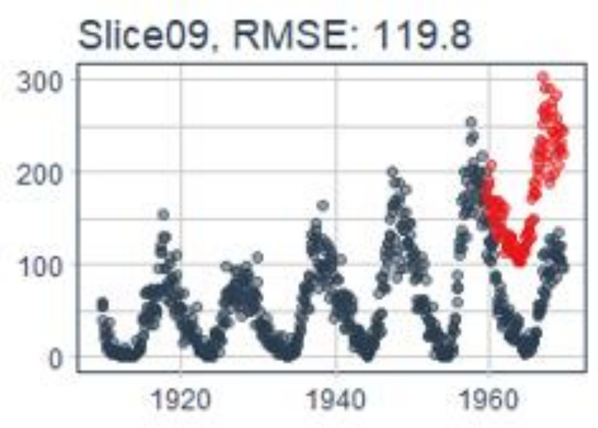
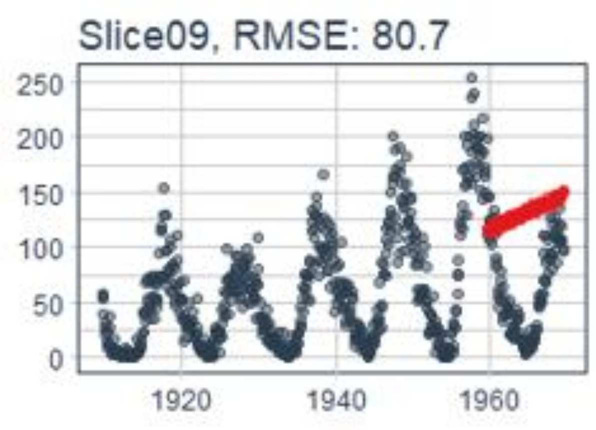
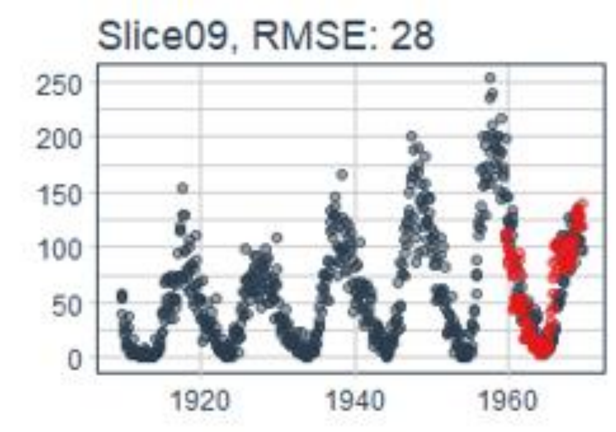
Keras LSTM Results

yardstick::rmse()

```
## # Rolling origin forecast resampling
## # A tibble: 11 x 2
##    id        rmse
##  * <chr>    <dbl>
##  1 Slice01   48.2
##  2 Slice02   17.4
##  3 Slice03   41.0
##  4 Slice04   26.6
##  5 Slice05   22.2
##  6 Slice06   49.0
##  7 Slice07   18.1
##  8 Slice08   54.9
##  9 Slice09   28.0
## 10 Slice10   38.4
## 11 Slice11   34.2
```

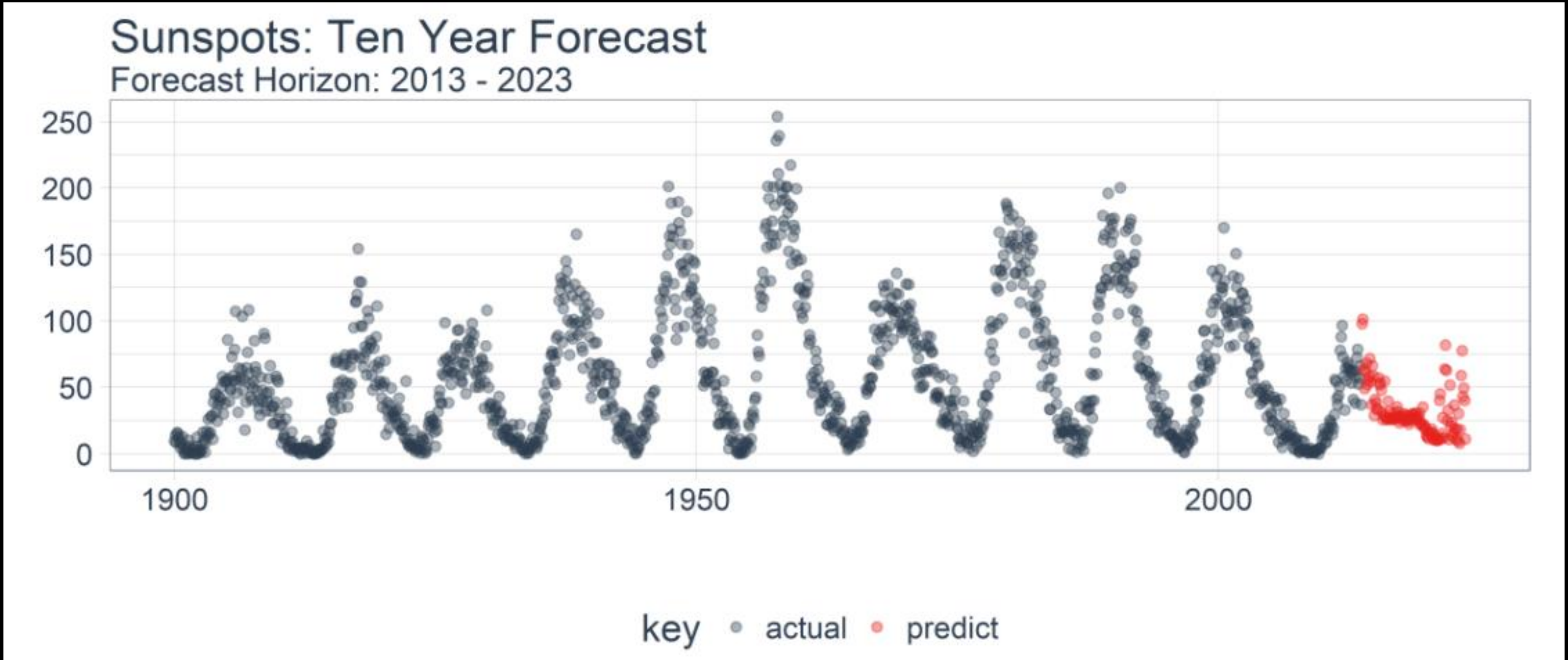


Technique Comparison

	ARIMA	Prophet	Keras LSTM
RMSE (Average)	50.5	45.3	34.4
RMSE (Std Dev)	27.3	19.7	13.0
Typical Model (Slice09)			

Keras Stateful LSTM: **32% Lower RMSE**

Forecasting Next 10 Years

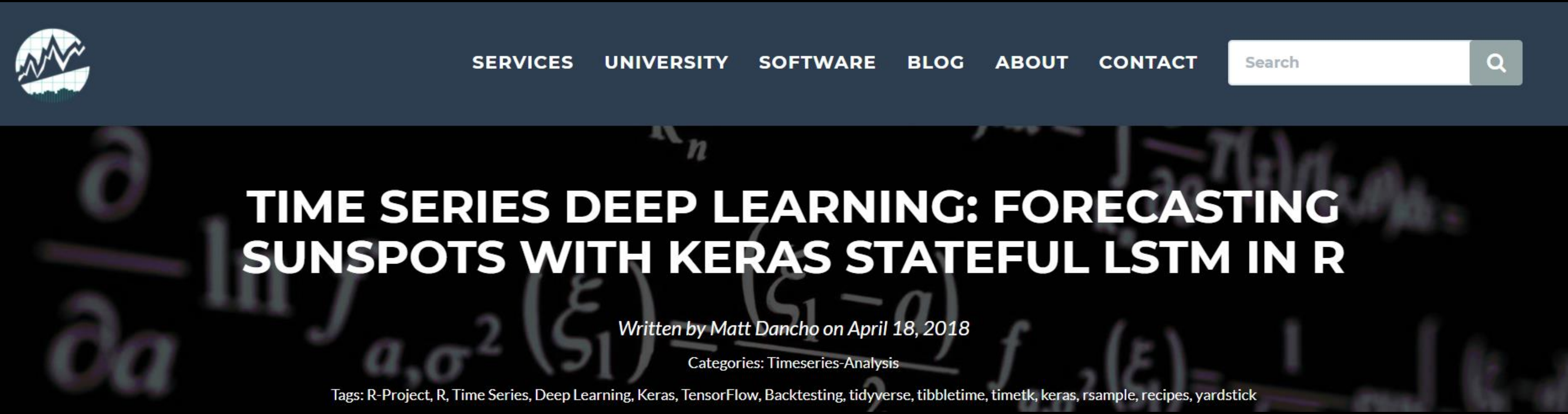


Conclusions

- Built a Stateful LSTM with Keras using Lag 120
- Benchmarked by Backtesting
- Compared to other techniques, 32% better RMSE
- Good Tool-Application Fit

Code Available

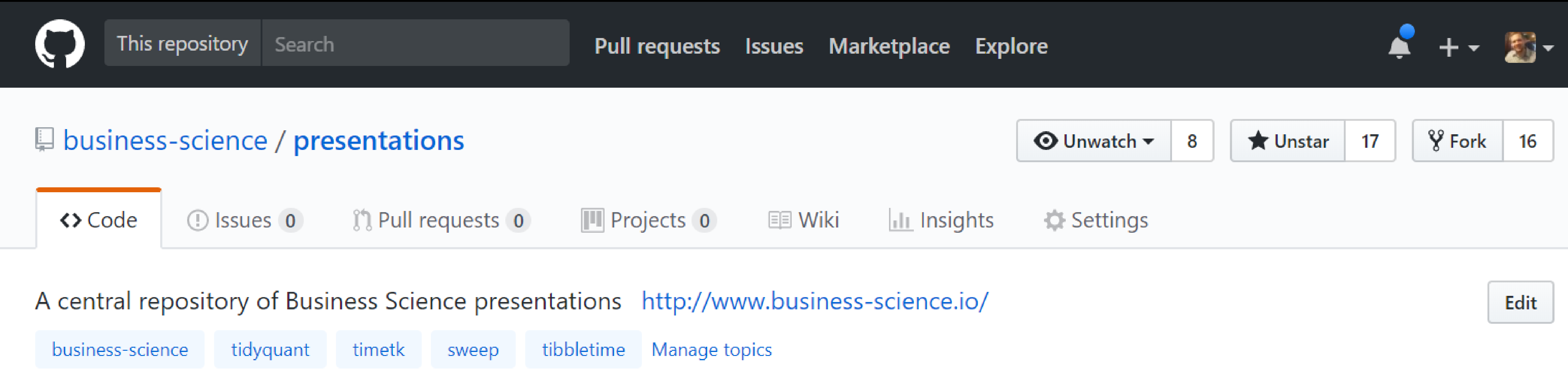
Business Science Blog



business-science.io/blog

Presentation Available

Business Science GitHub



https://github.com/business-science/presentations

Business + Data Science

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