ECOTS 2018

INTRODUCTION TO R/RSTUDIO FOR NEW USERS

OUTLINE

- Part I: Personal Background
- Part II: For Students with No Background in Programming
- Part III: For Those Educating Students with No Background in Programming
- Part IV: For Those with a Background in Programming
- Appendix: External Resources

PART I

PERSONAL BACKGROUND

CHRISTOPHER PETER MAKRIS

- Studied Logic, Discrete Mathematics, & Statistics
- Graduate of Master's of Statistical Practice Program at Carnegie Mellon University
- Data Scientist
- Director of Data Science
- Programs Administrator; Adjunct Instructor Department of Statistics & Data Science at CMU


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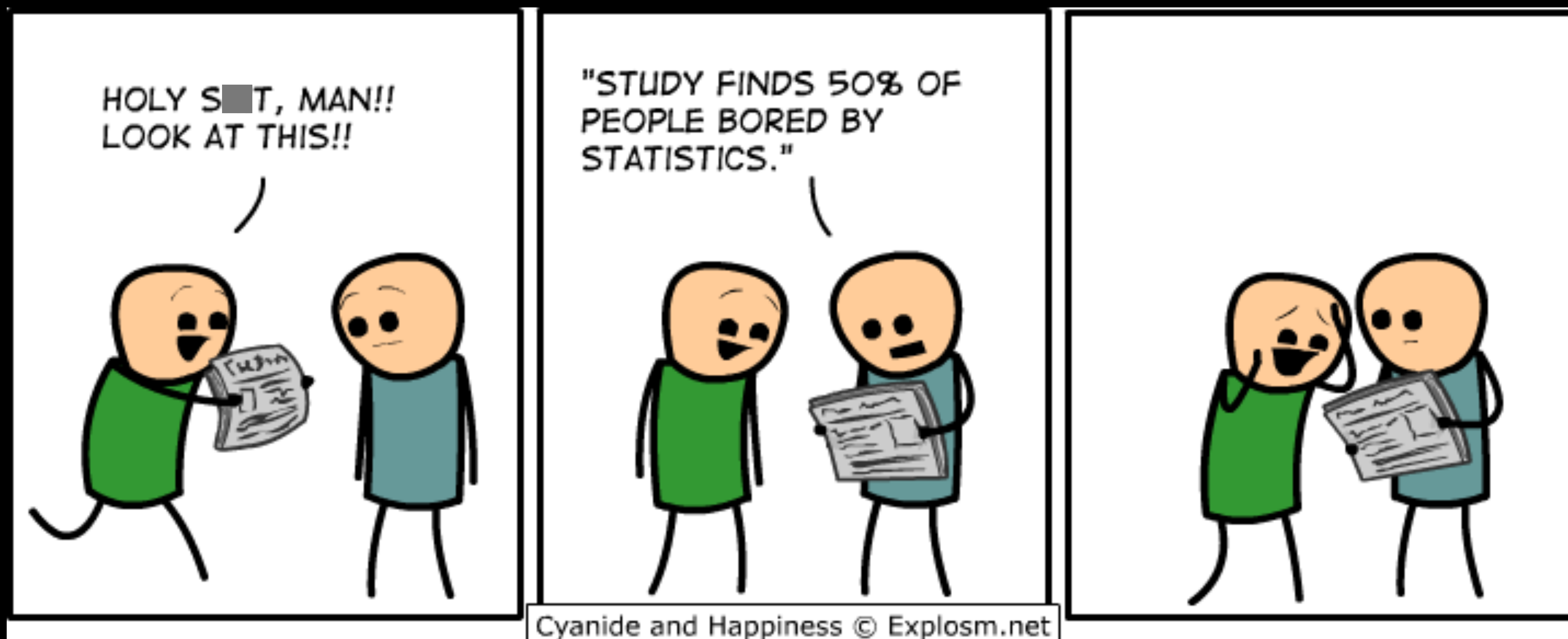
"STUDY FINDS 50% OF PEOPLE BORED BY STATISTICS."
Cyanide and Happiness © Explosm.net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Statistics & Data Science

Object Types

Functions

Data Visualization

Statistics & Data Science

Data Transformations

Writing Scripts

EDA & Modeling

Statistics & Data Science

R/RStudio

PART II

FOR STUDENTS WITH NO BACKGROUND IN PROGRAMMING

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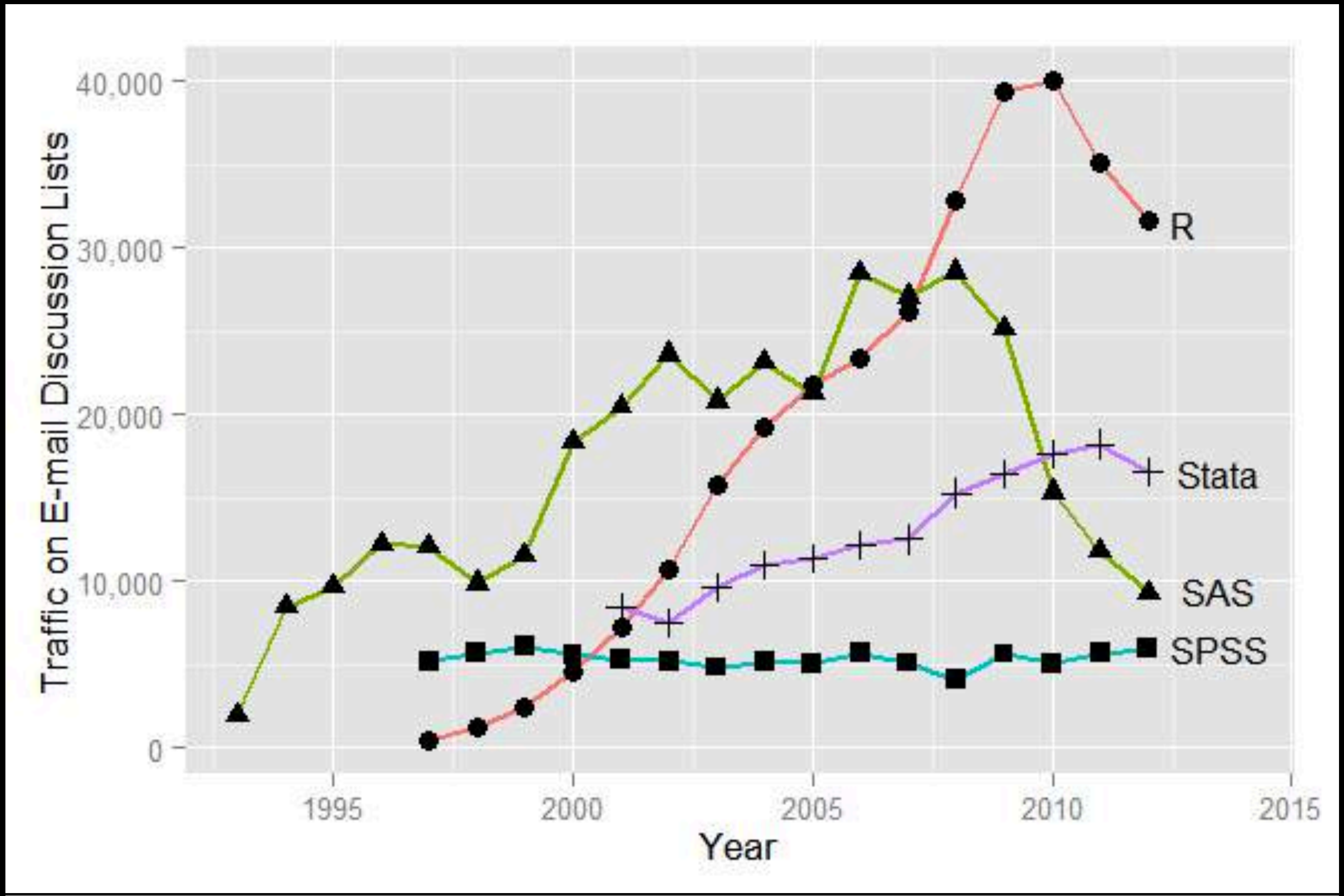
    - Updates to the core versions of R are relatively frequent, reflecting the growth of the field.

GROWTH IN POPULARITY OF R



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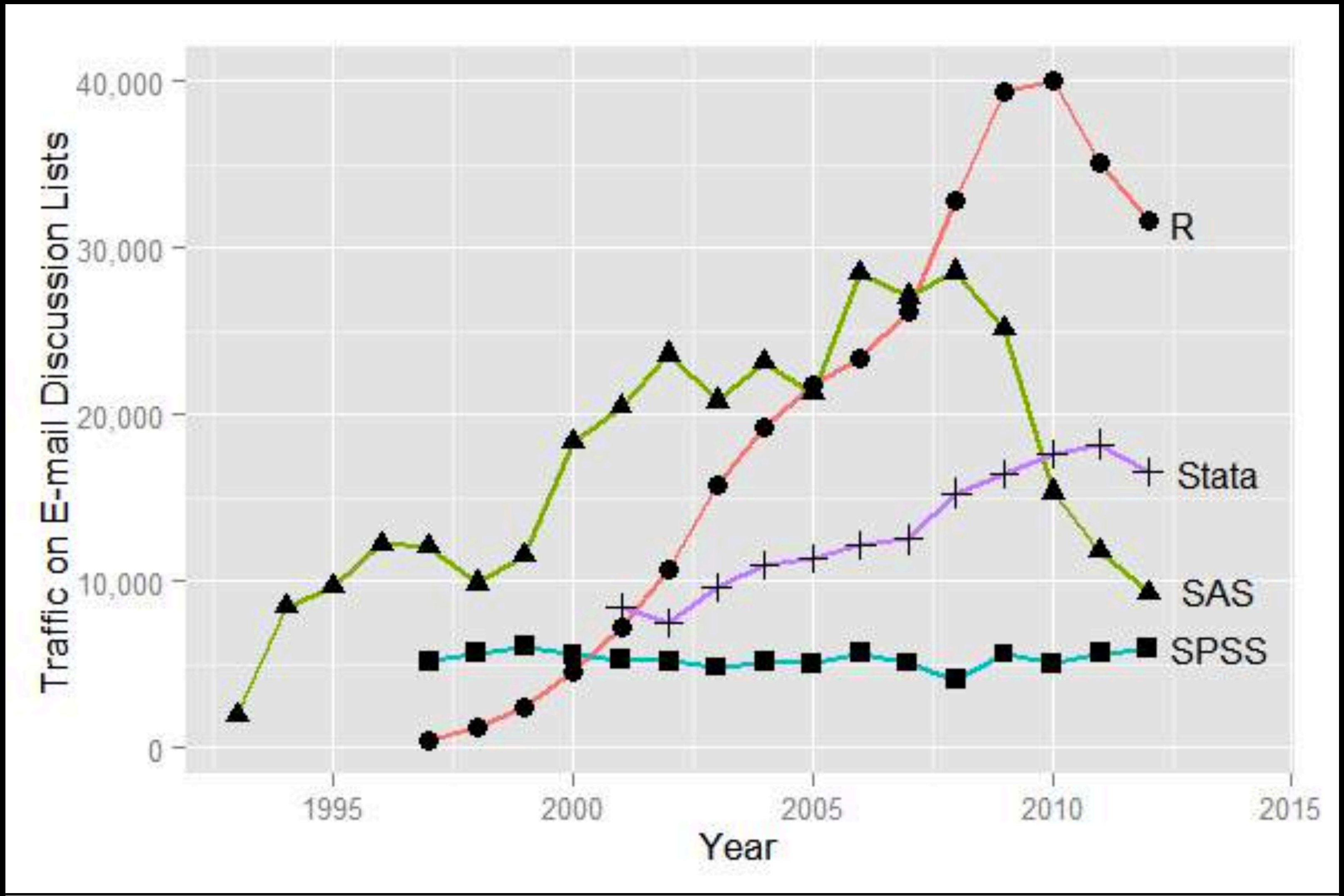

- Sum of monthly email traffic on each software's main listserv discussion list. (Robert A. Muenchen, StatsBlogs)


OPEN


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6. `summary(mydata[,"x"])`
7. `summary(mydata[["x"]])`
8. `summary(mydata[1])`
9. `summary(mydata[[1]])`
10. `attach(mydata); summary(x)`
11. `summary(select(mydata, x))`
12. `mydata %>% with(summary(x))`
13. `mydata %>% summary(.$x)`
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        - Analyze observations with subsets with `group_by()`.

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- Consistency in properties allows for the chaining of multiple simple steps in order to produce a complex result.

PART III

FOR THOSE EDUCATING STUDENTS WITH NO BACKGROUND IN PROGRAMMING

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- Solution: Personify to relate a non-programming concept to learning R.

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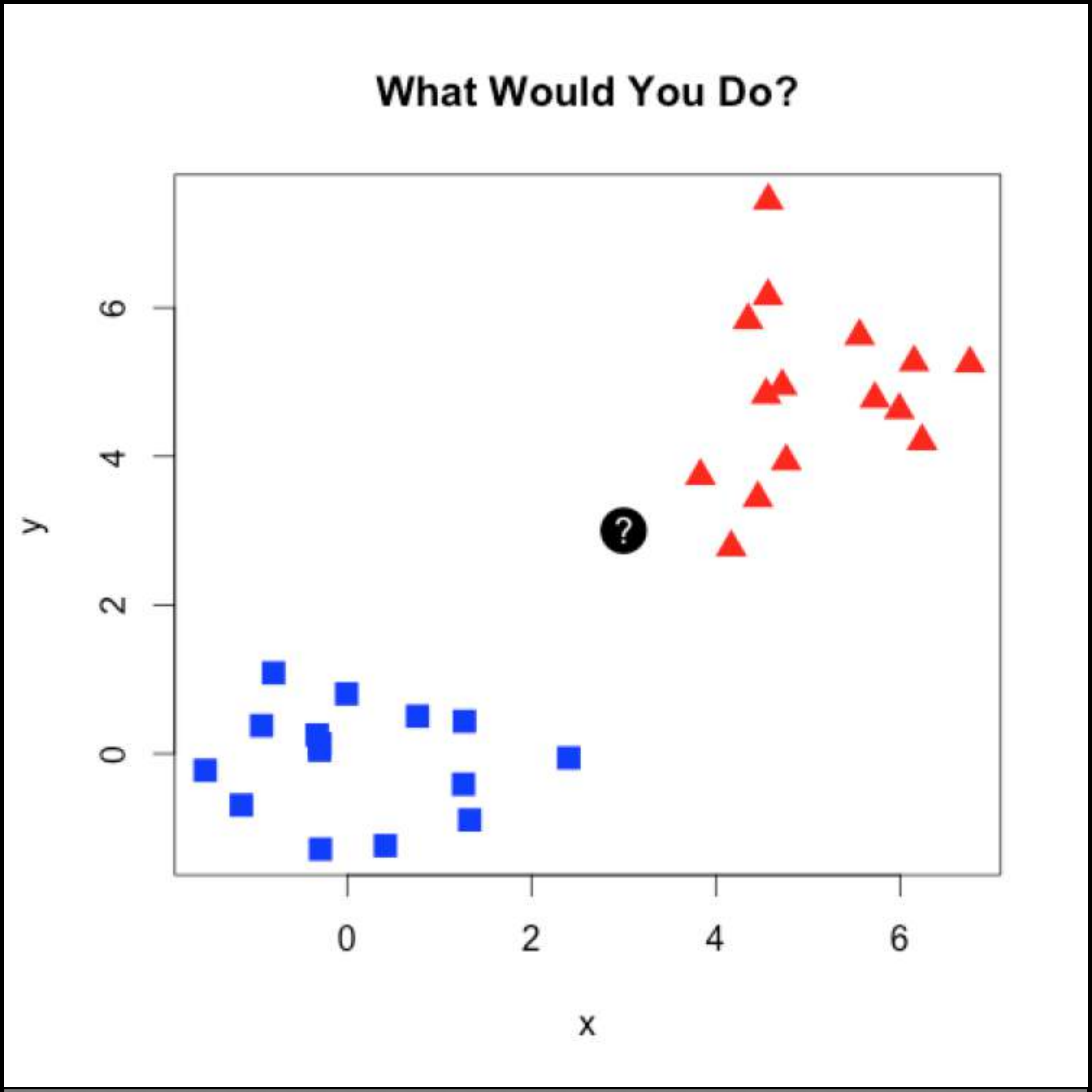

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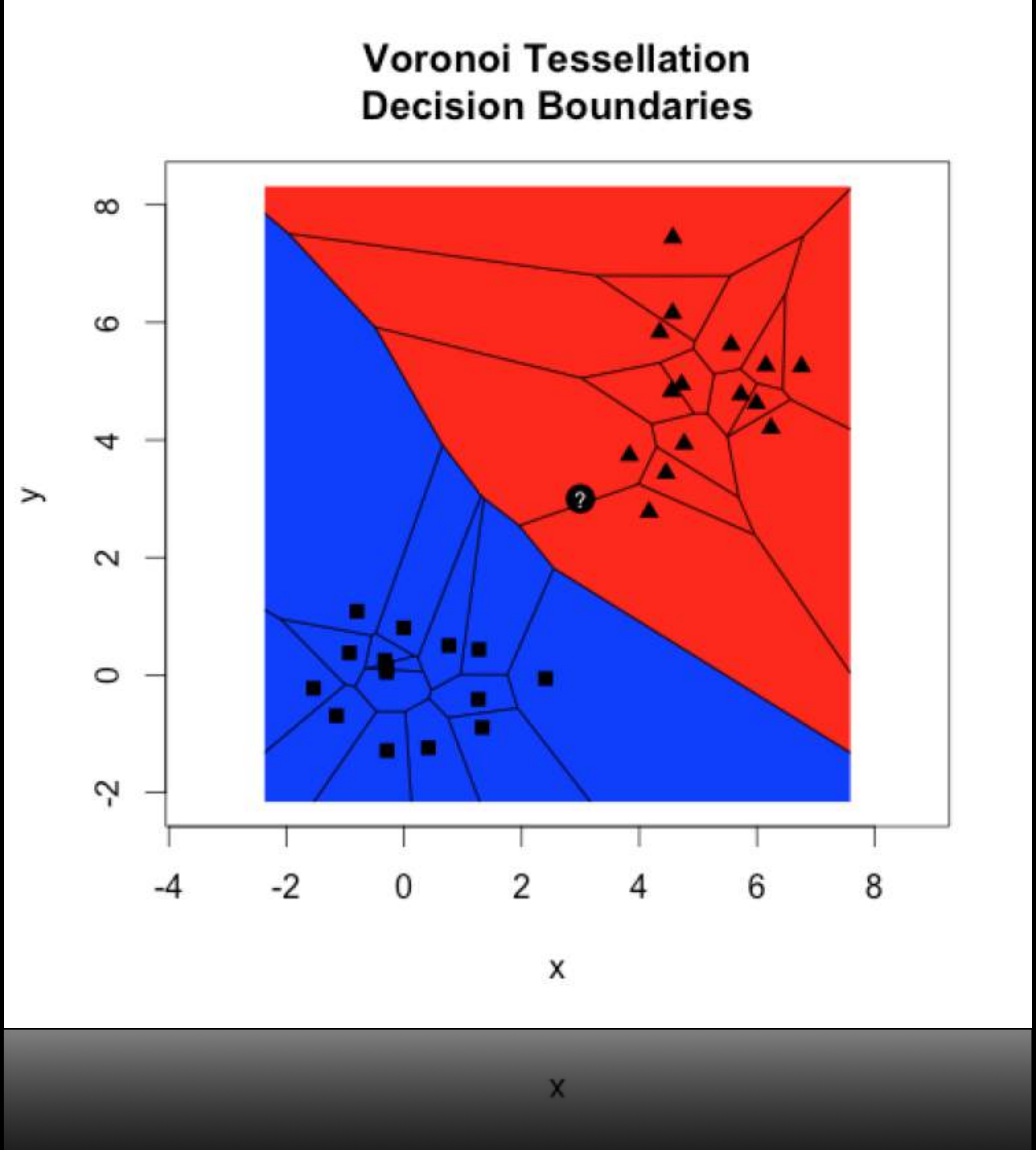

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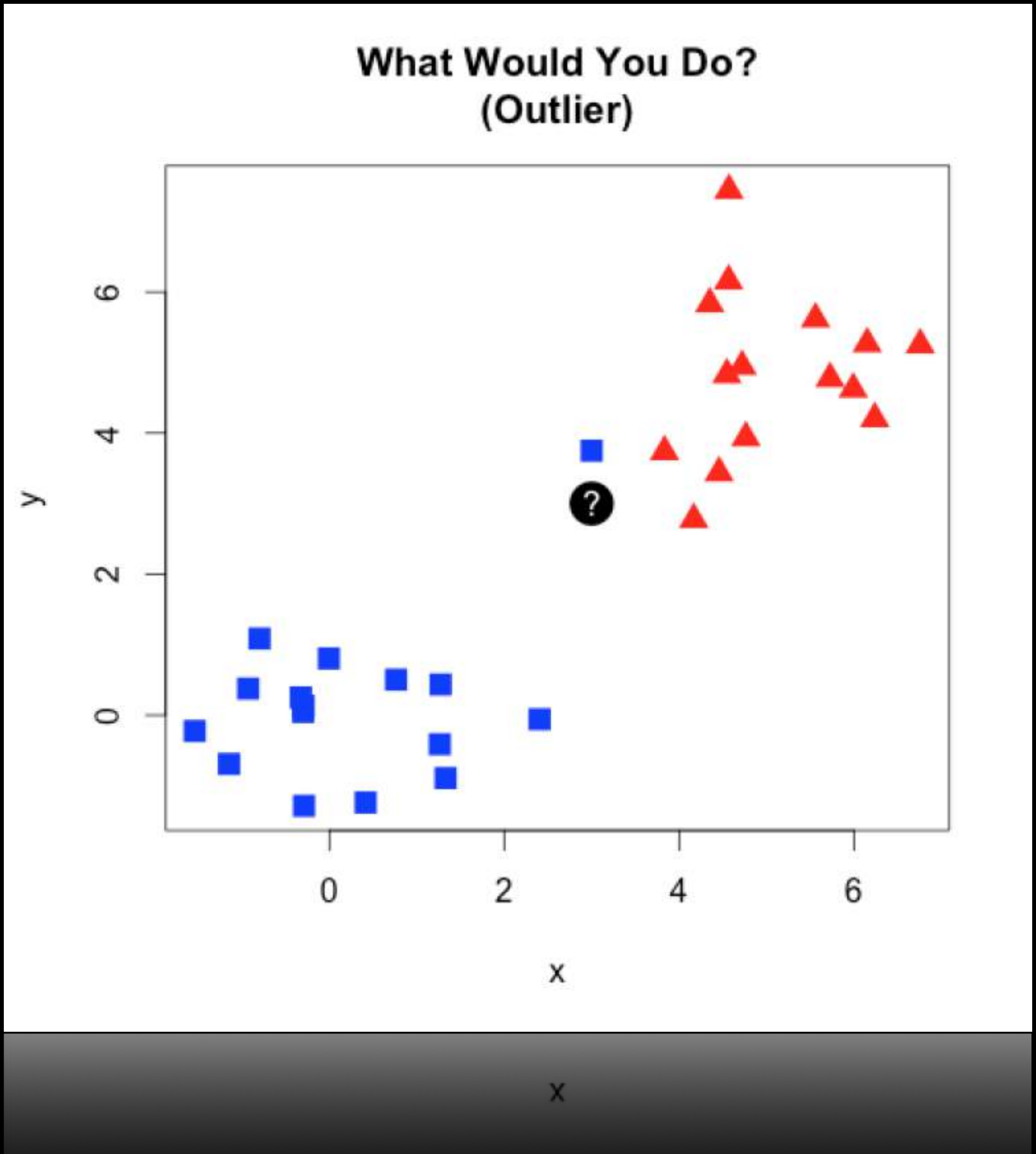

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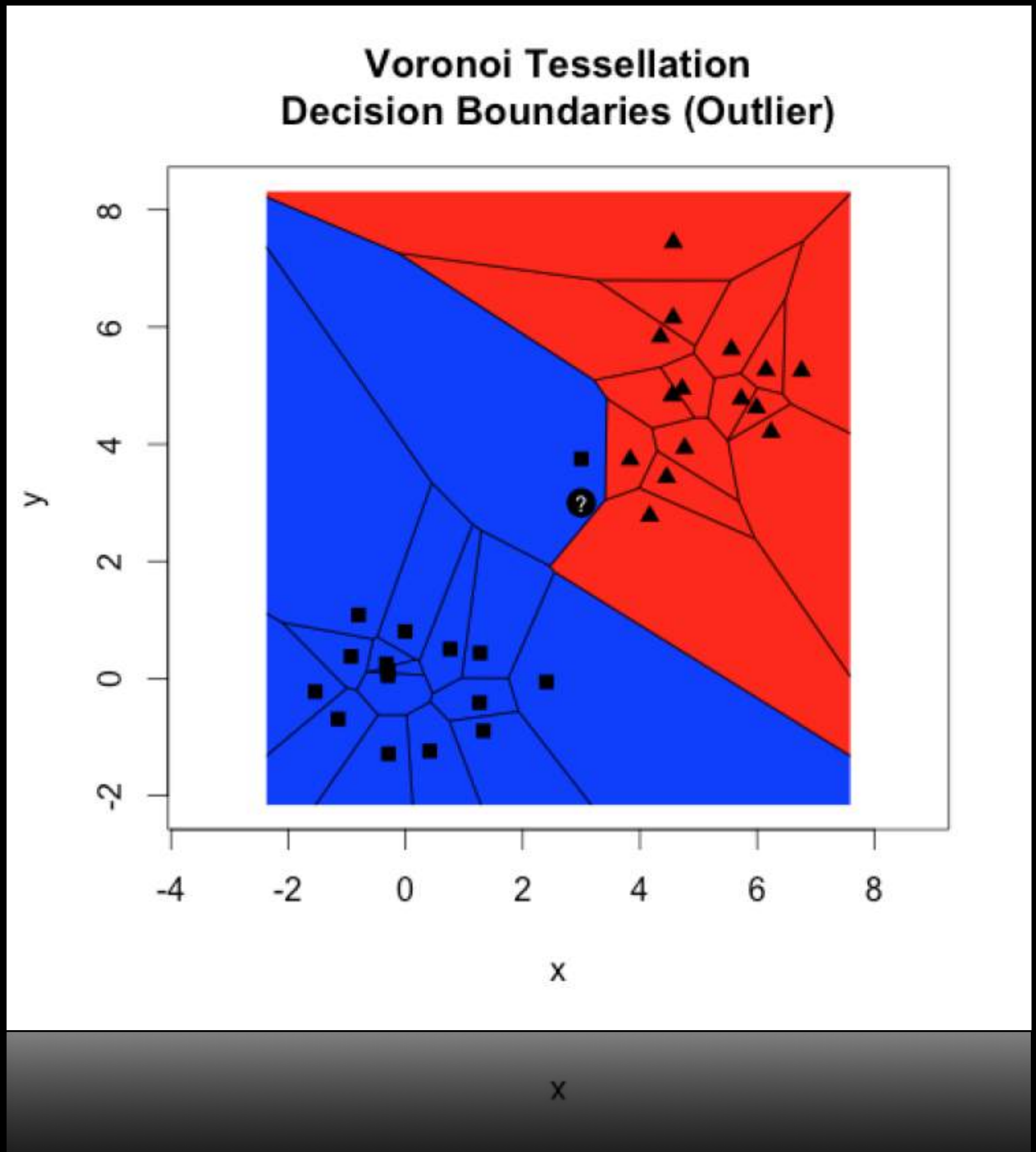

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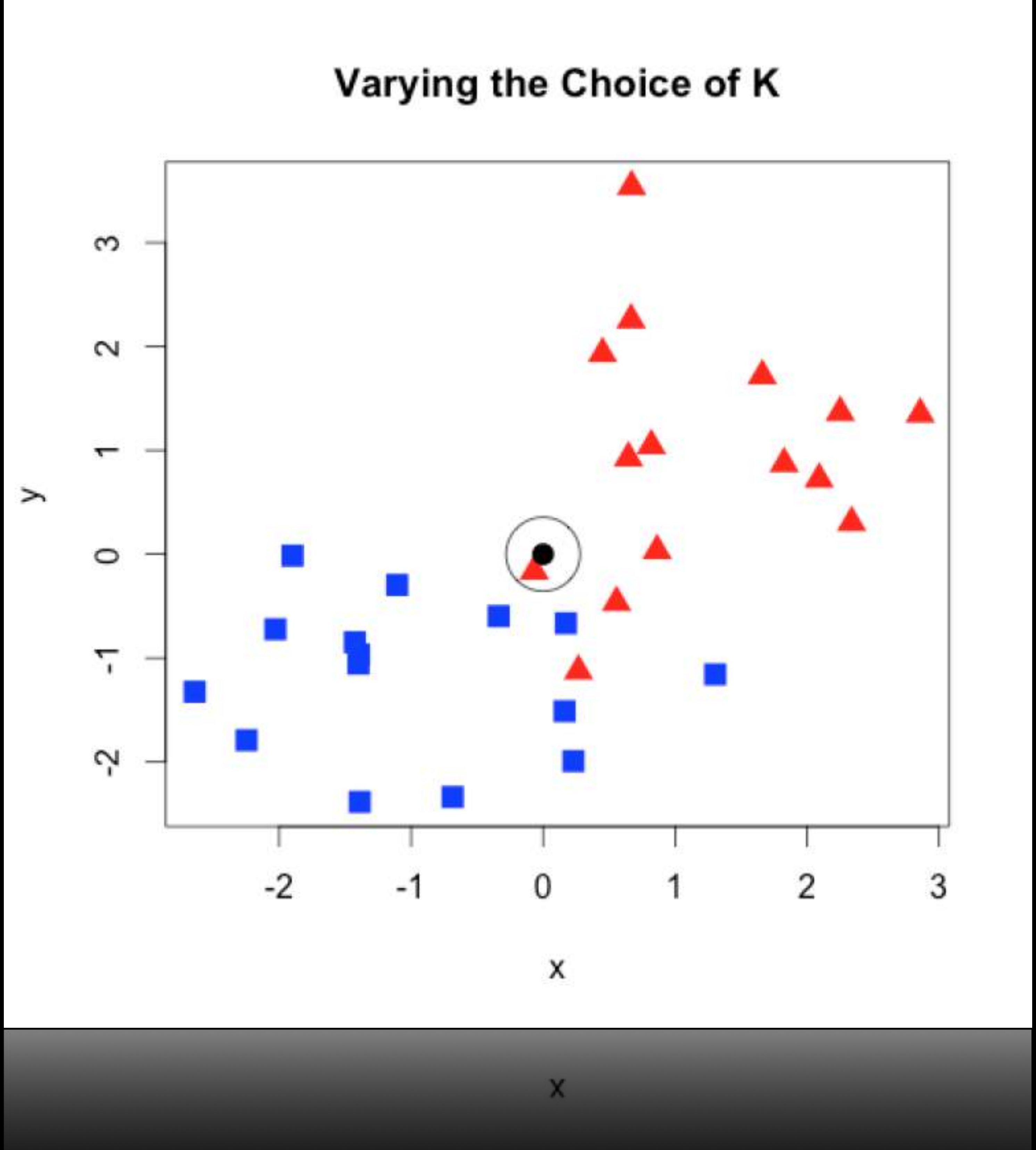

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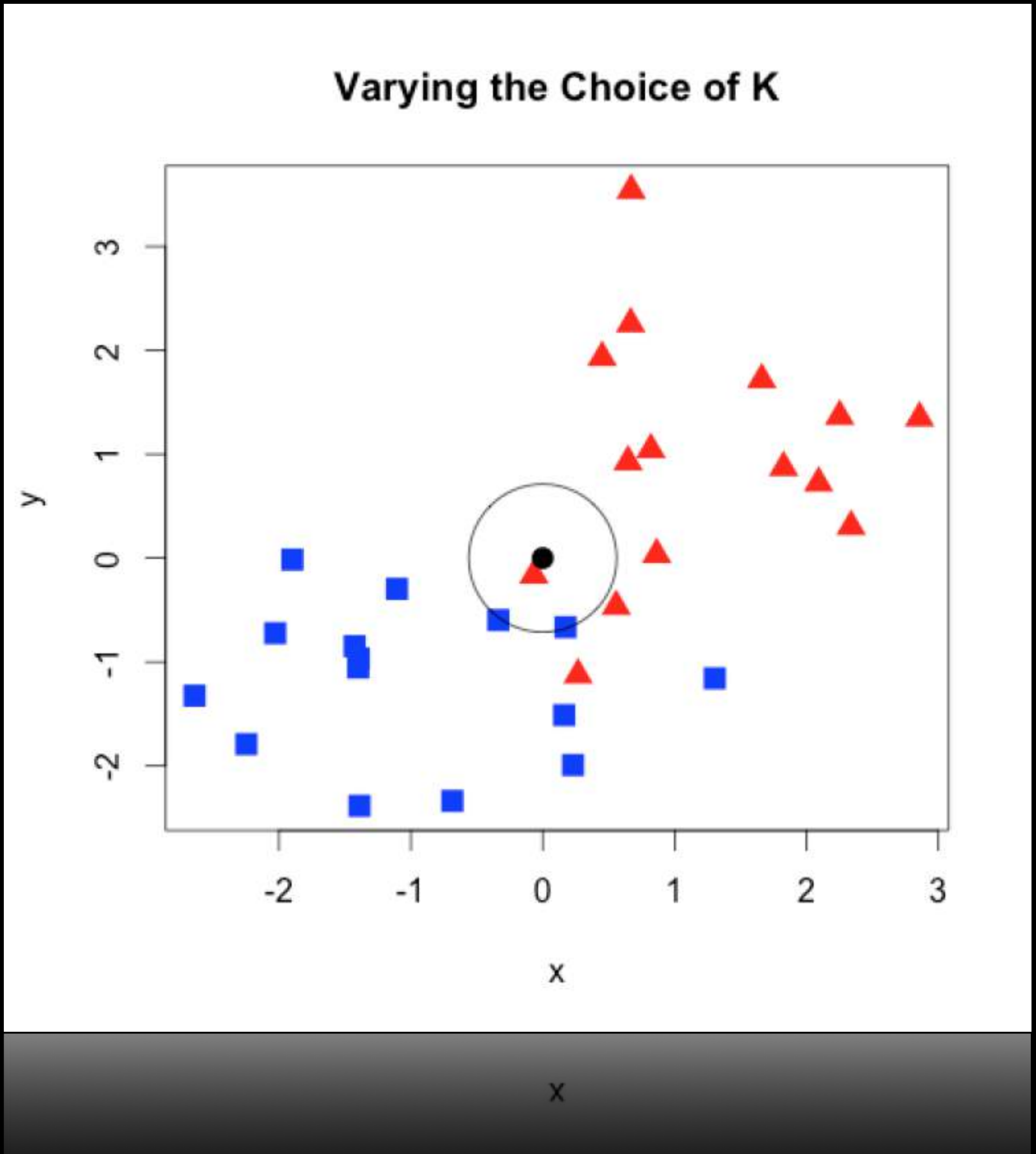

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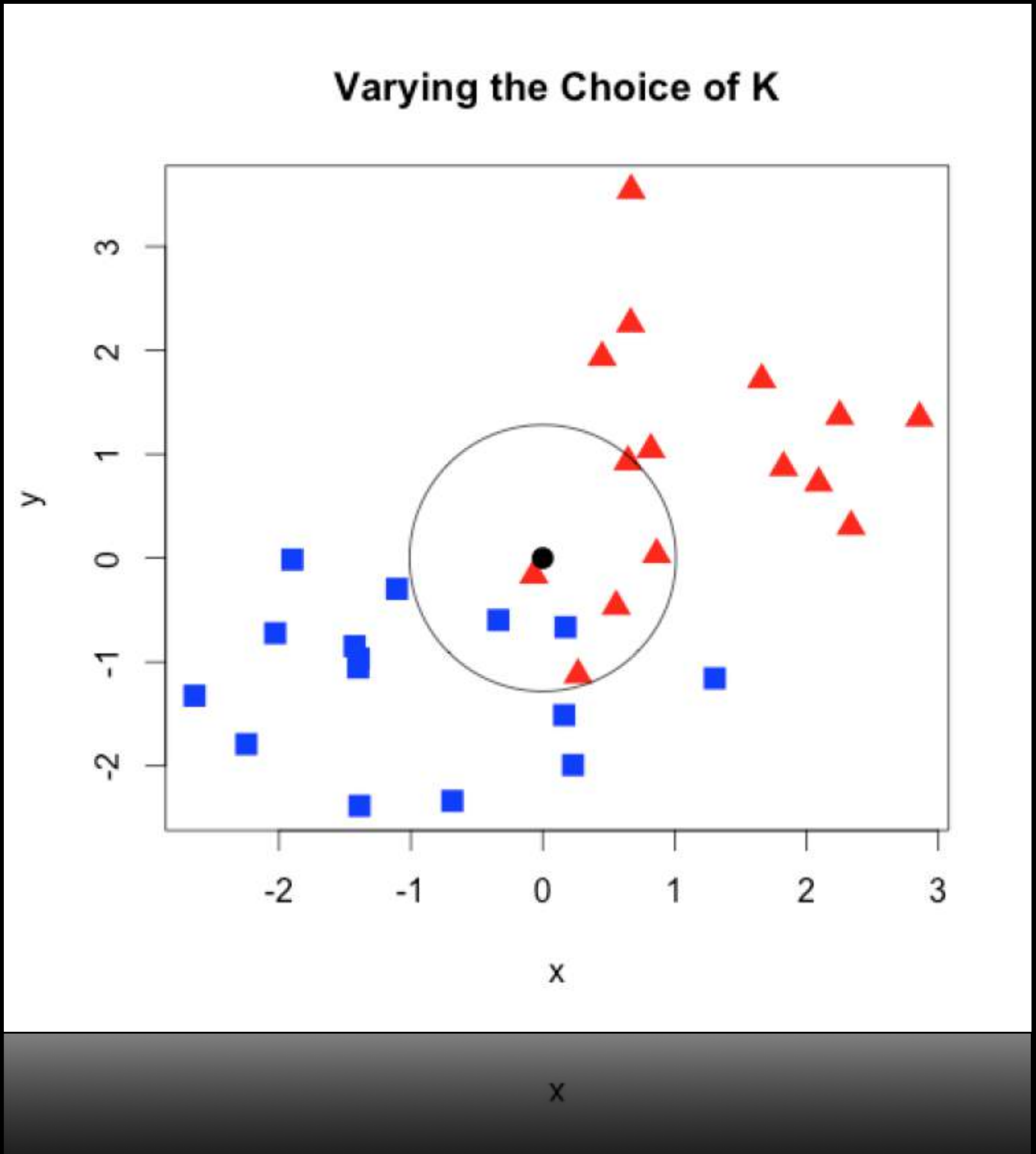

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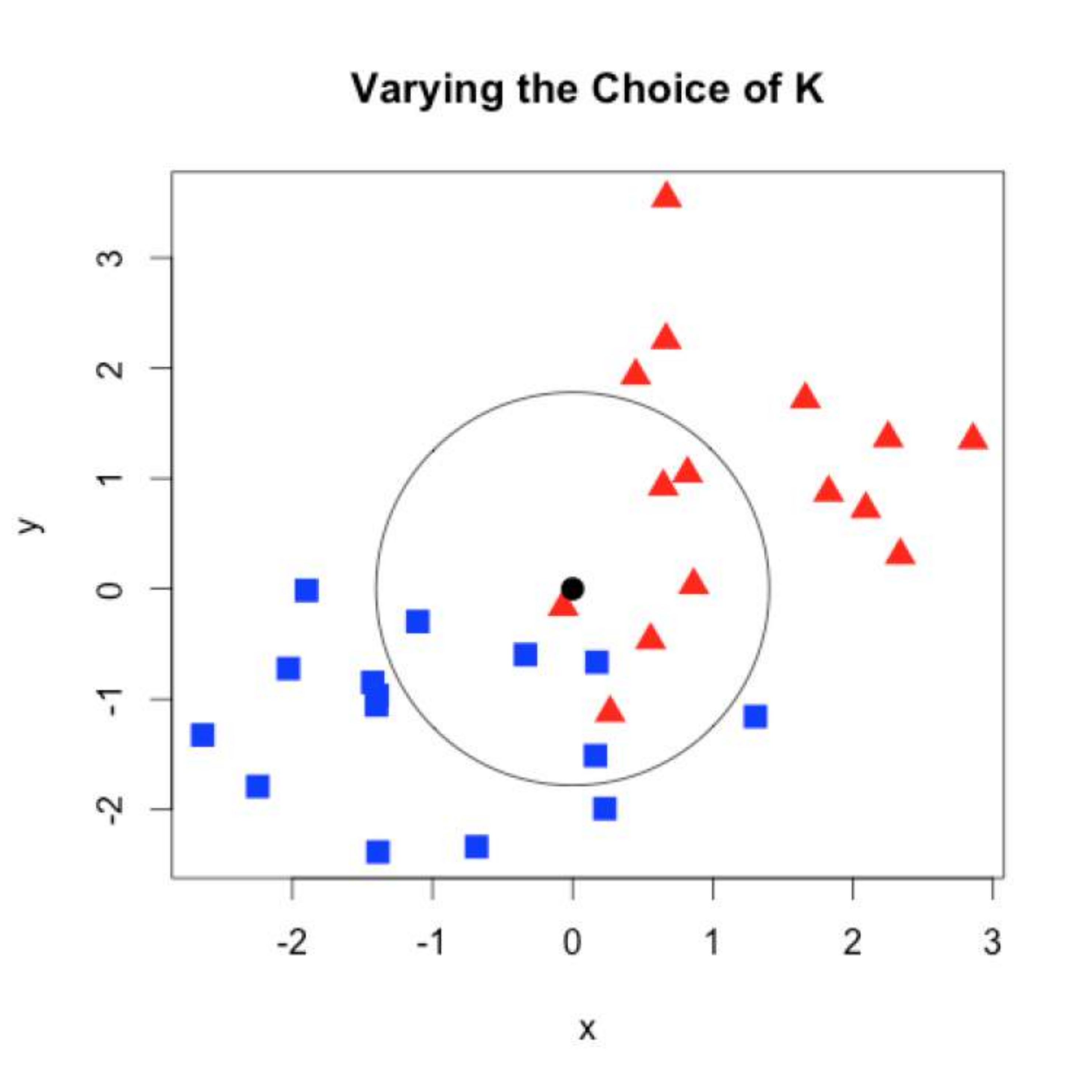
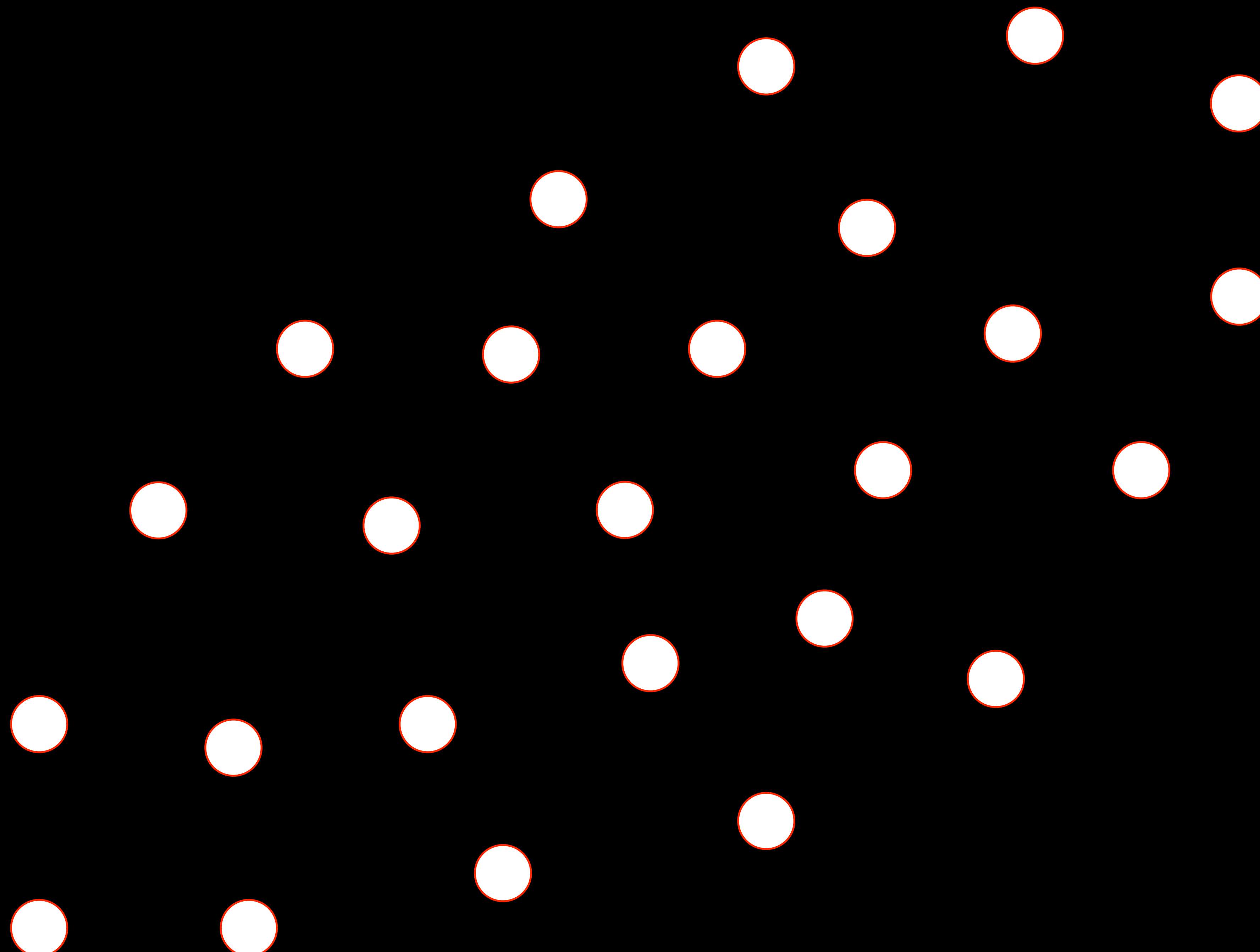
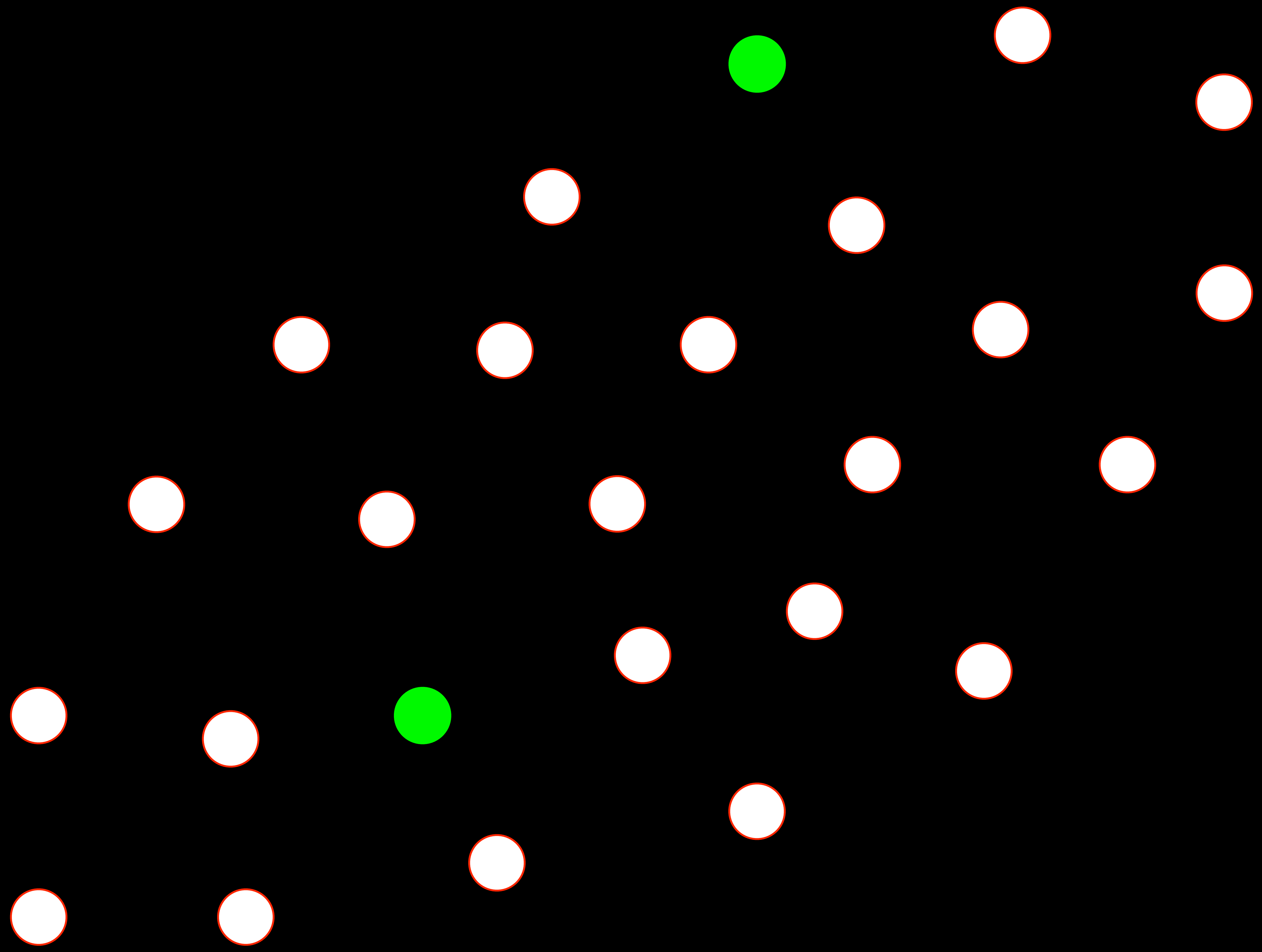
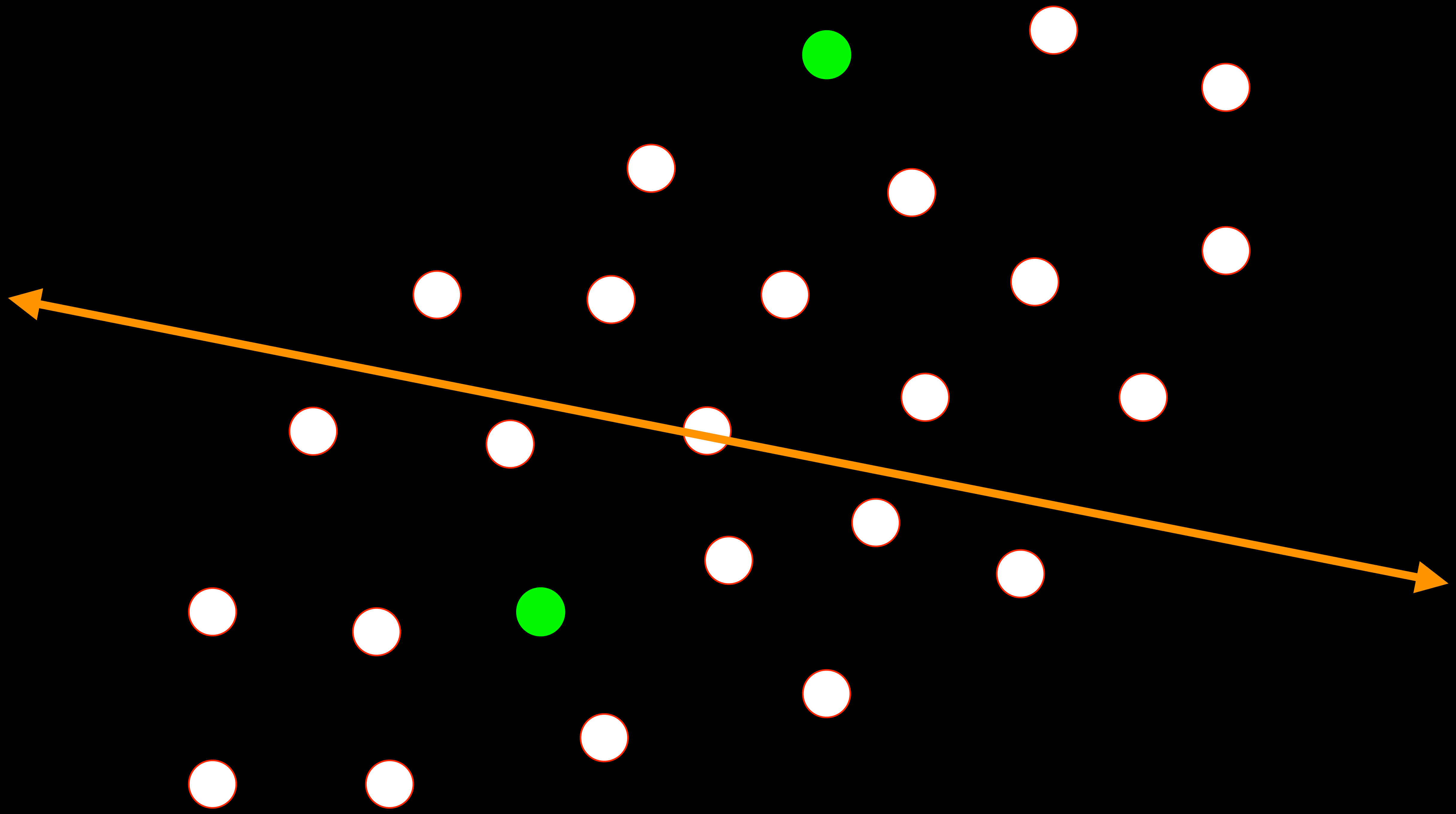
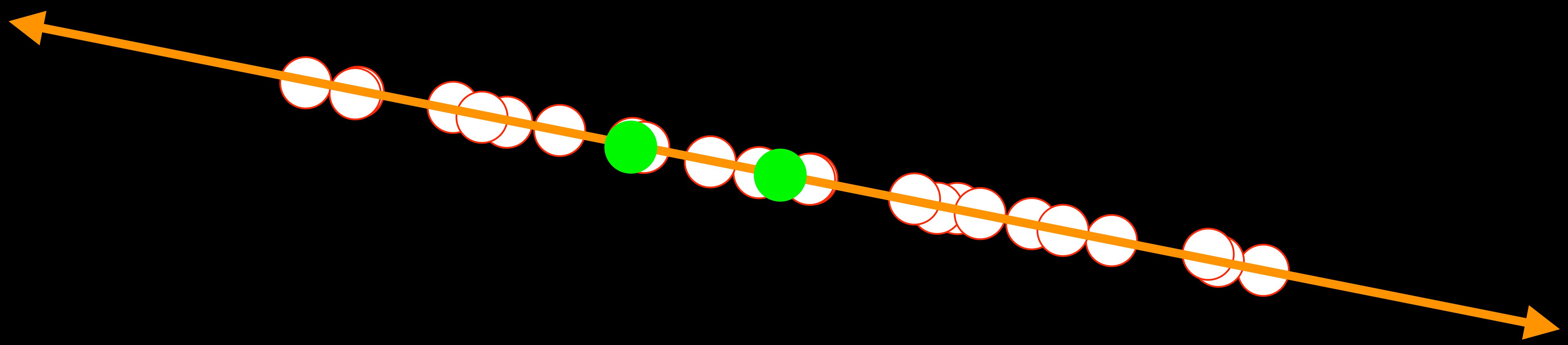
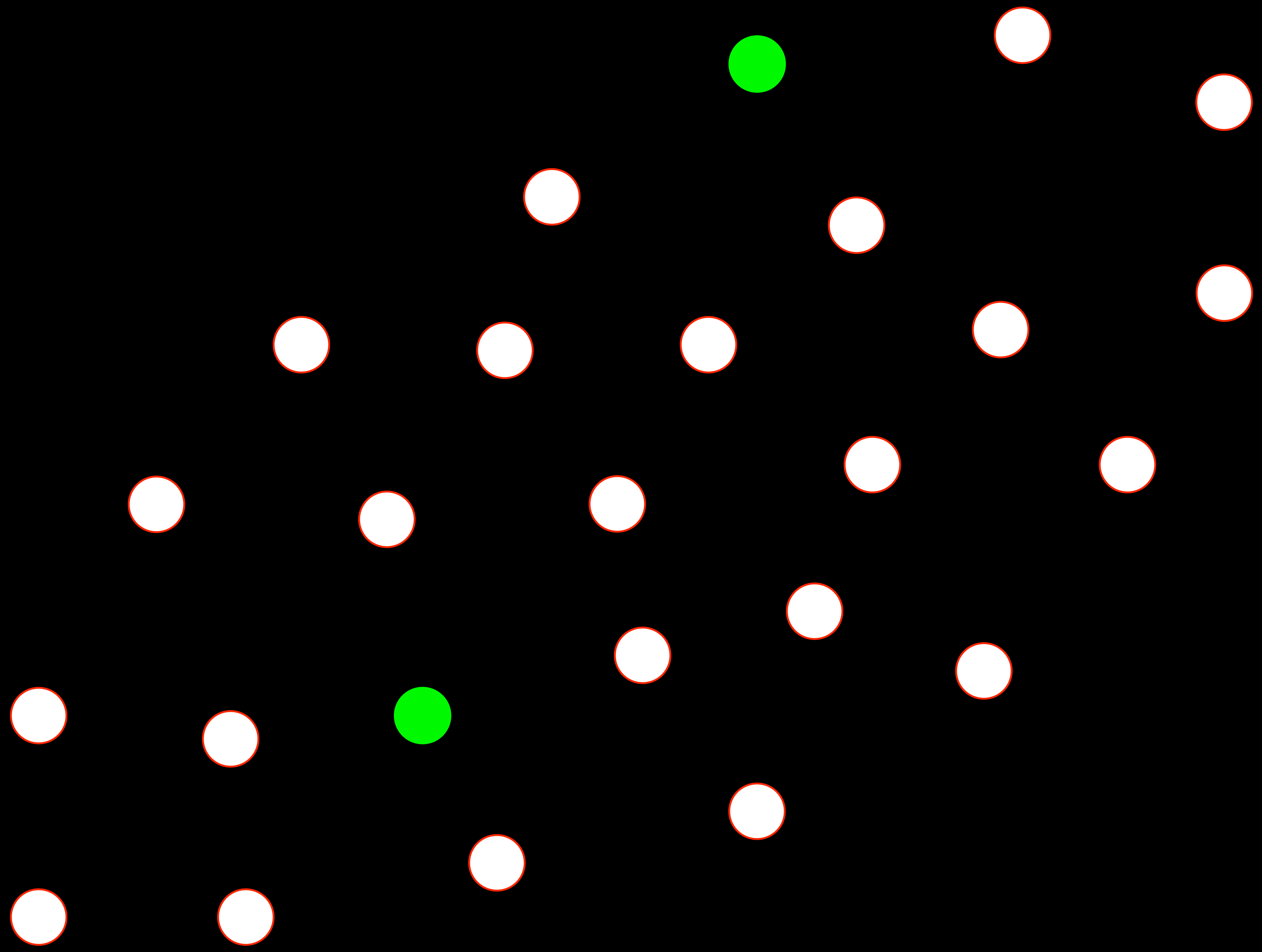


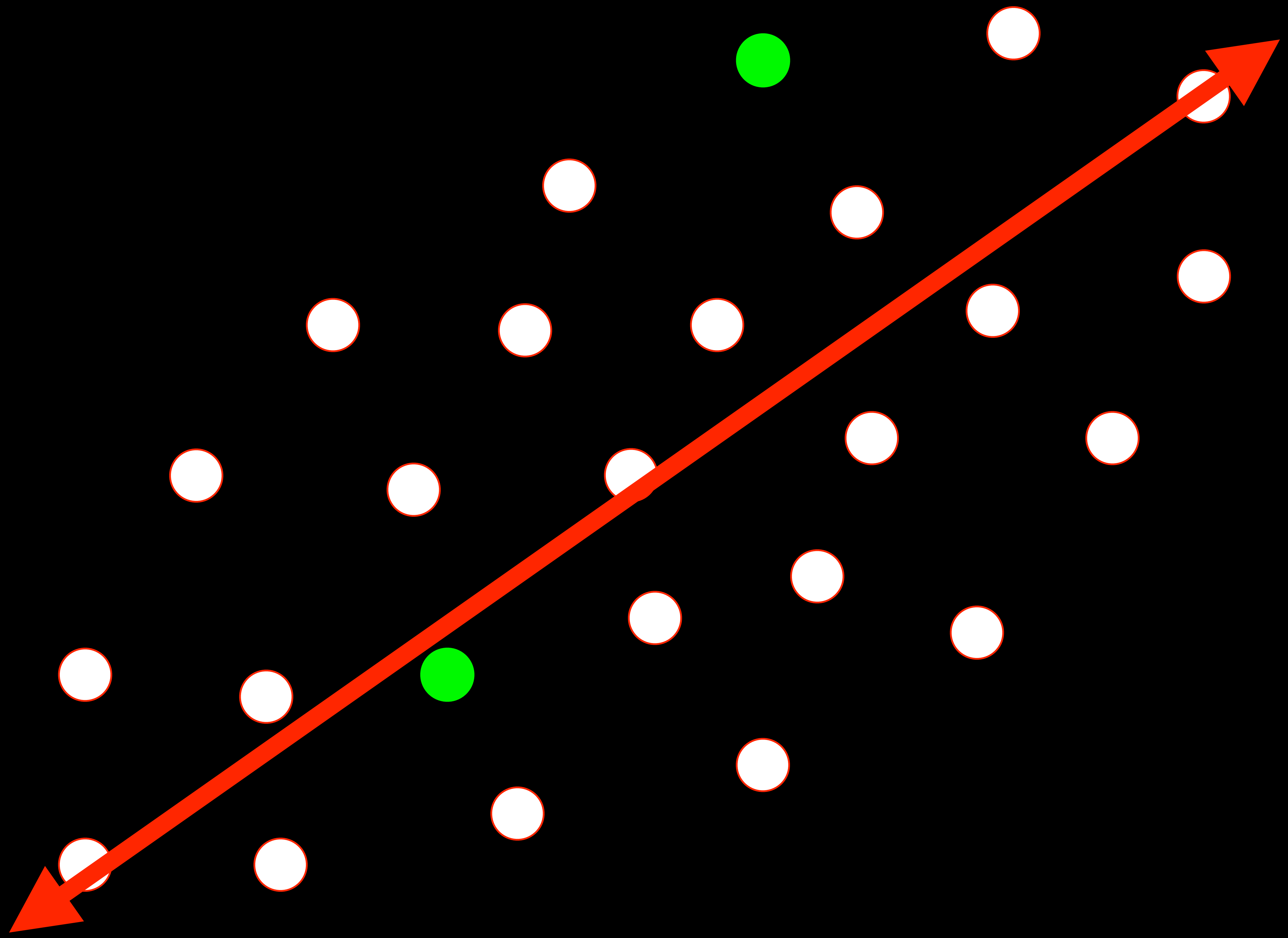


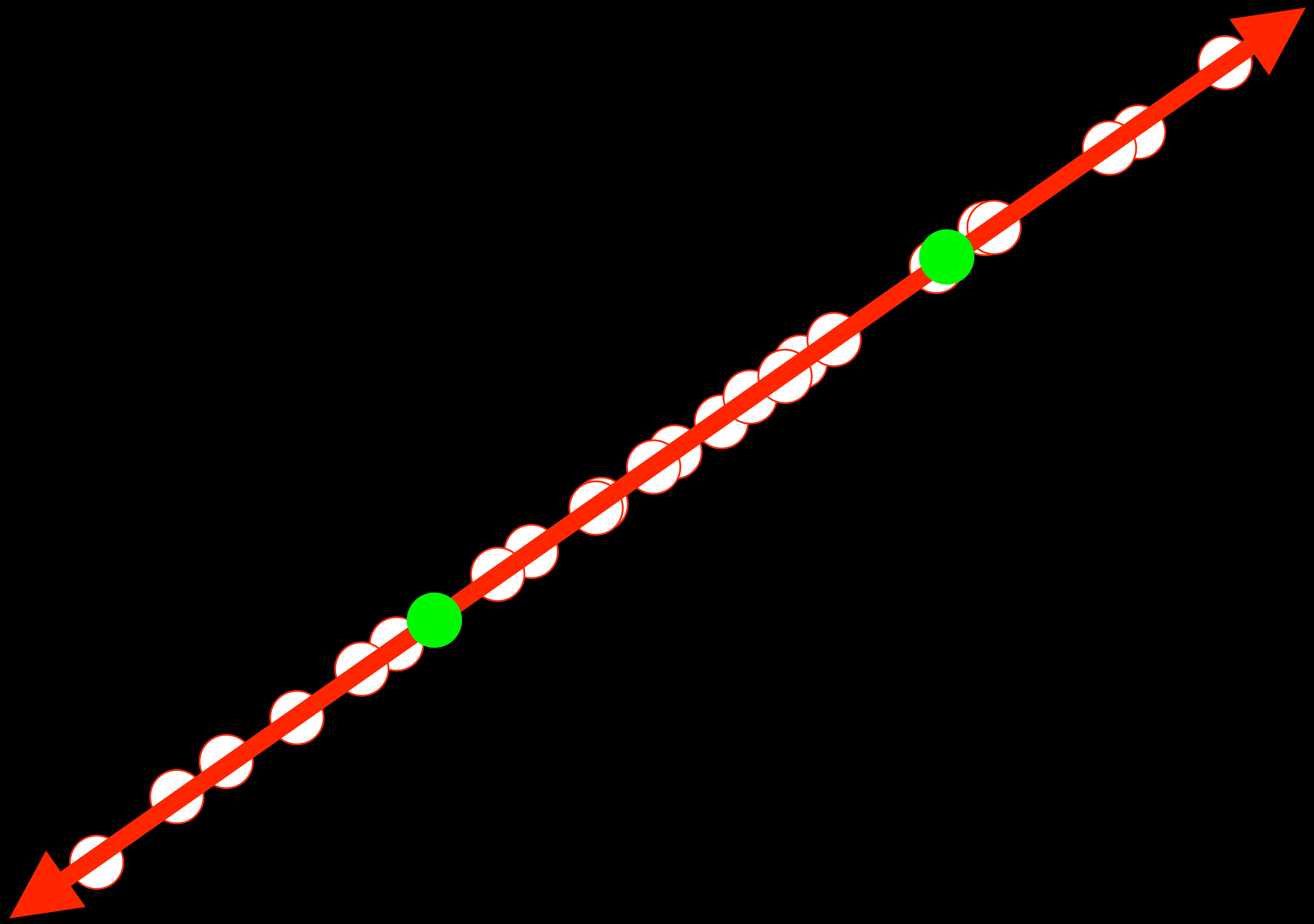


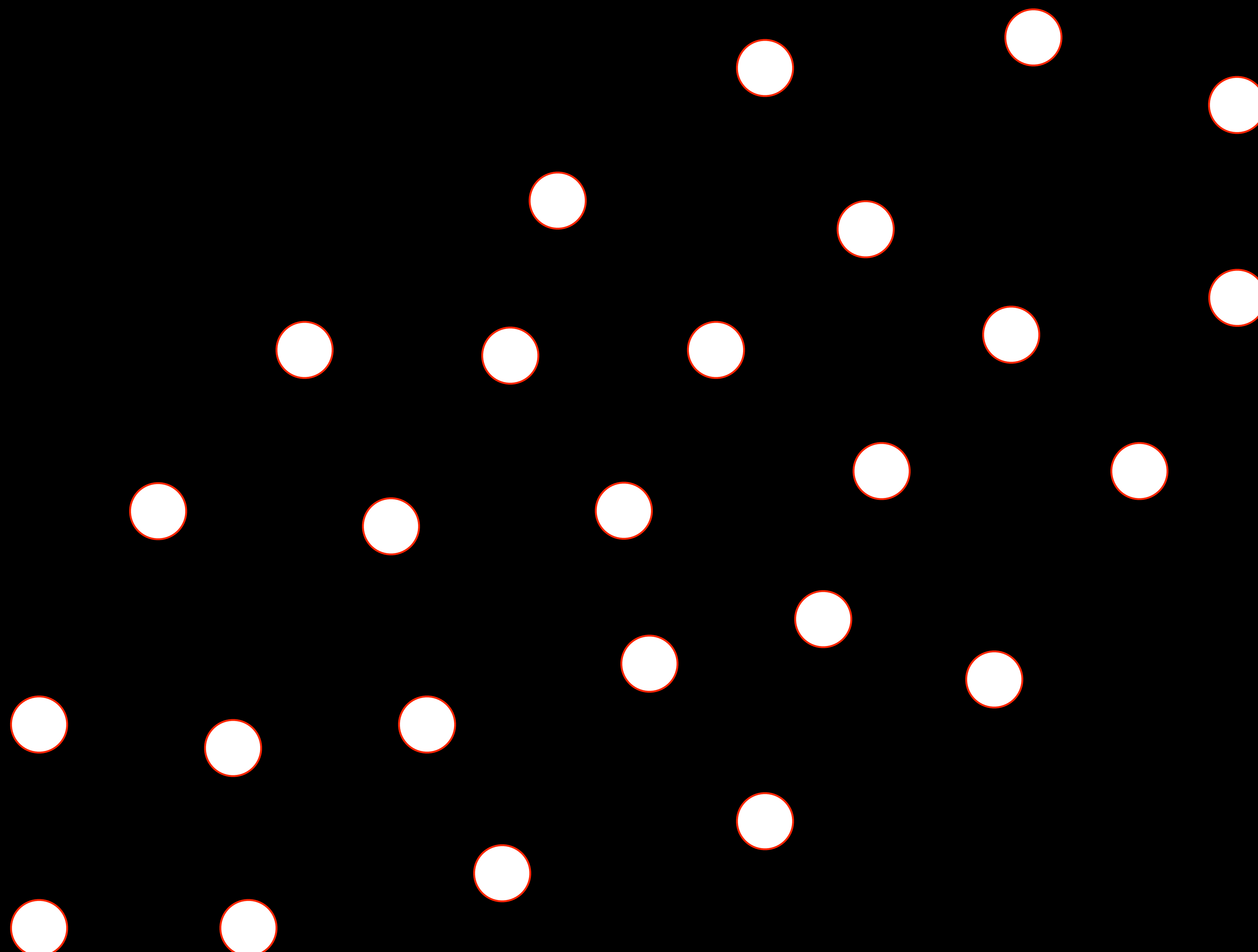


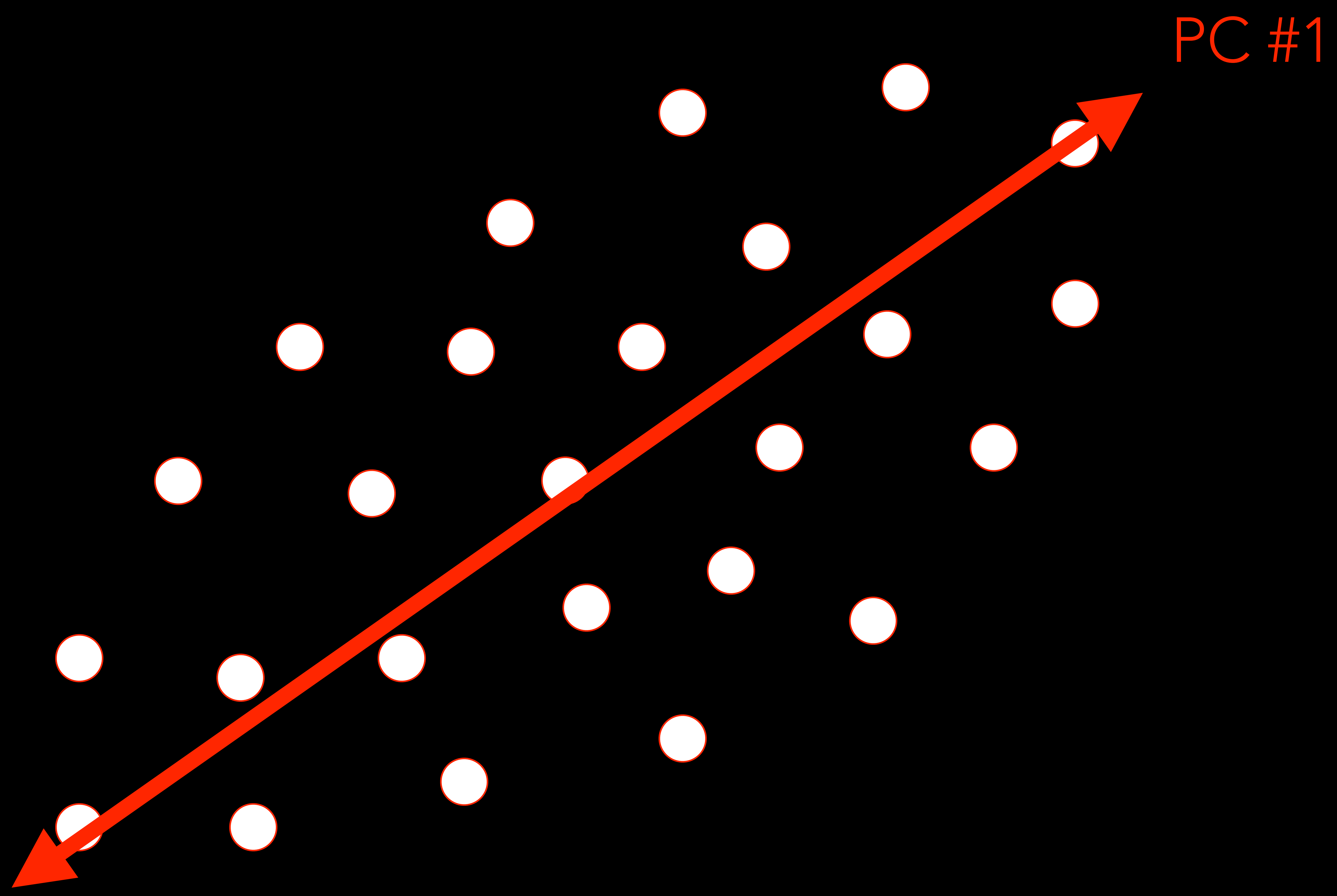


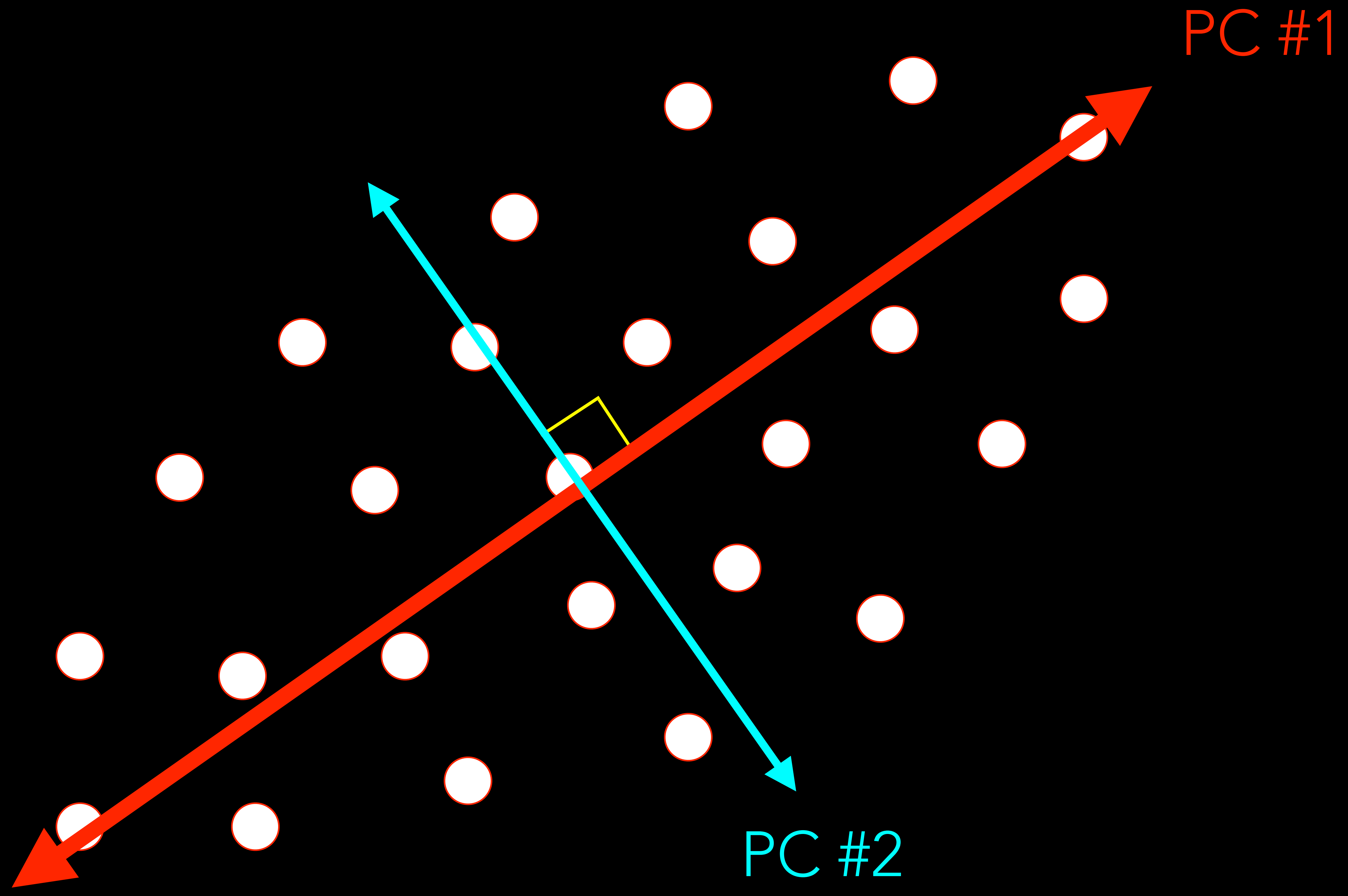


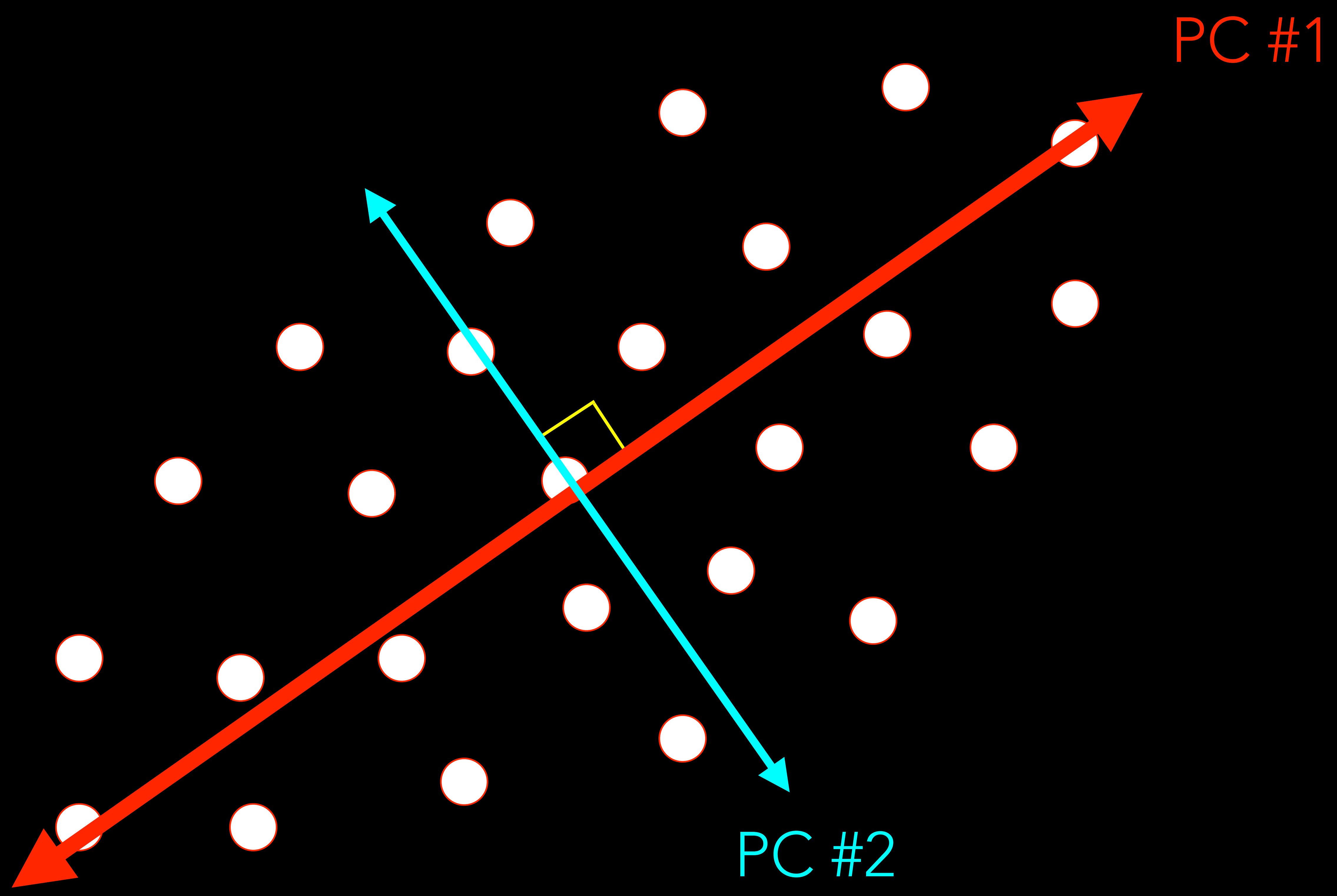







PC #1


PC #1
PC #2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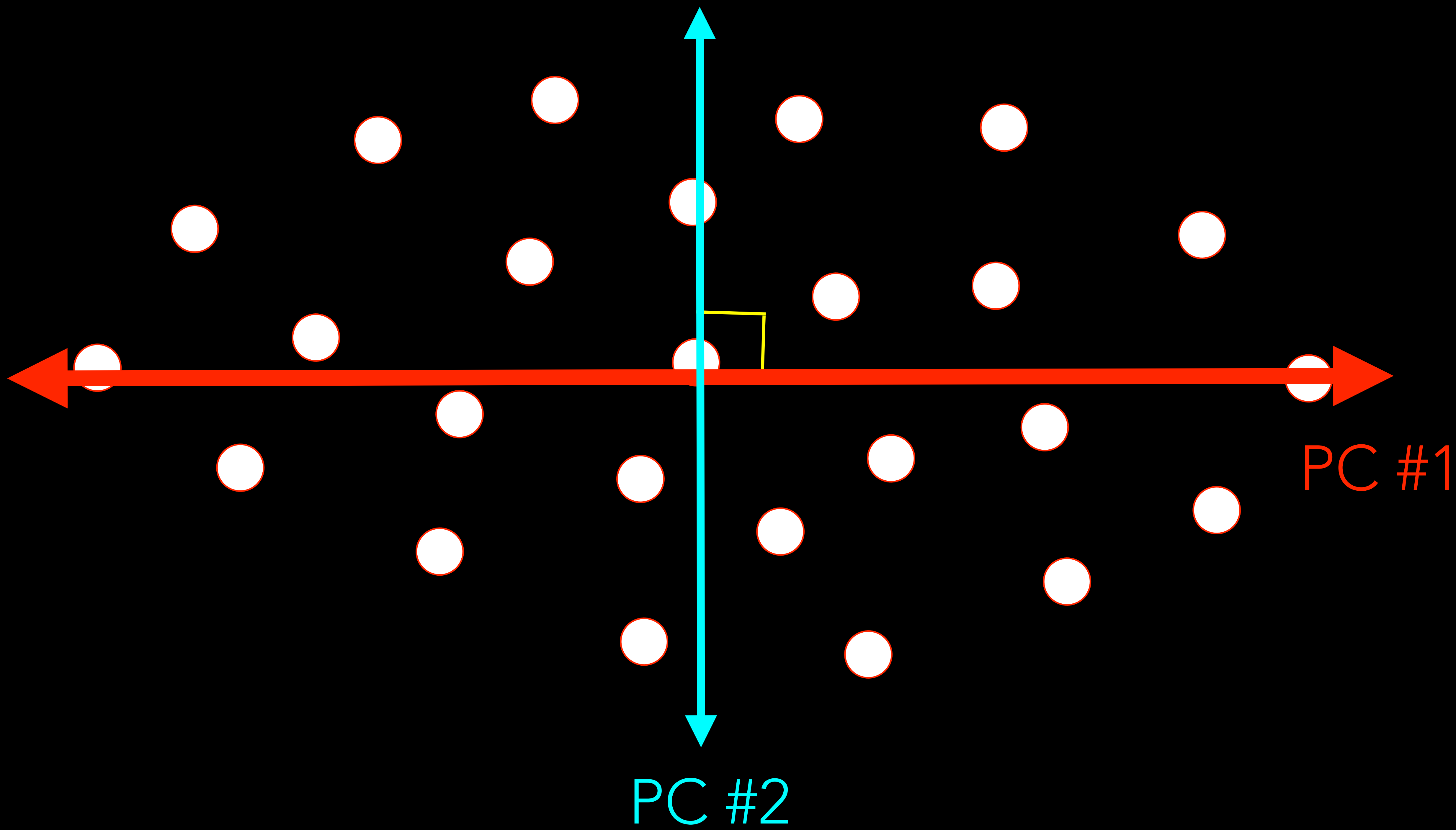
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PART IV

FOR THOSE WITH A BACKGROUND IN PROGRAMMING

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EXTERNAL RESOURCES

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- *R for Data Science* (Hadley Wickham & Garrett Grolemund)
    - "You'll learn how to get your data into R, get it into the most useful structure, transform it, visualize it and model it."
- *The Book of R* (Tilman M. Davies)
    - "*The Book of R* is a comprehensive, beginner-friendly guide to R…you'll find everything you need to begin using R effectively for statistical analysis."
- swirl (Nick Carchedi, Brian Caffo, Sean Kross, et al.)
    - "swirl teaches you R programming and data science interactively, at your own pace, and right in the R console!"
- RStatistics.net
    - "An educational resource for all things related to R language and its applications in advanced statistical computing and machine learning."
- *An Introduction to R* (Bill Venables & David Smith)
- Quick-R (Robert I. Kabacoff)

"Thank you!"

-CHRISTOPHER PETER MAKRIS