

# Text Analysis for Legal Practice

## (Class 4)

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[github.com/cdcrabtree/uvashortcourse](https://github.com/cdcrabtree/uvashortcourse)  
[bit.ly/2FSRGO7](https://bit.ly/2FSRGO7)

# Class Outline

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## Key R packages

- `stm`

# Single vs. Mixed Membership Models

## Clustering

Document  $\rightsquigarrow$  one cluster

Doc 1

Doc 2

Doc 3

Doc  $N$

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# What is Topic Modeling?

**Topic modeling** is an algorithm used to code the content of a corpus into substantively meaningful categories, or “topics,” using the statistical correlations between words.

It is unsupervised because we don't tell it the topics beforehand. The algorithm “discovers” abstract topics that can be thought of as a constellation of words that tend to show up together.

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# Let's Program

Launch RStudio and we can get started programming.

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