Clustering & Retrieval:

A machine learning perspective

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Machine Learning Specialization
University of Washington

Part of a specialization

This course is a part of the Machine Learning Specialization

What is the course about?

What is retrieval?

Search for related items

Input x,{x'}:
features for
query point
+
features of
all other datapoints

Compute distances to other x'

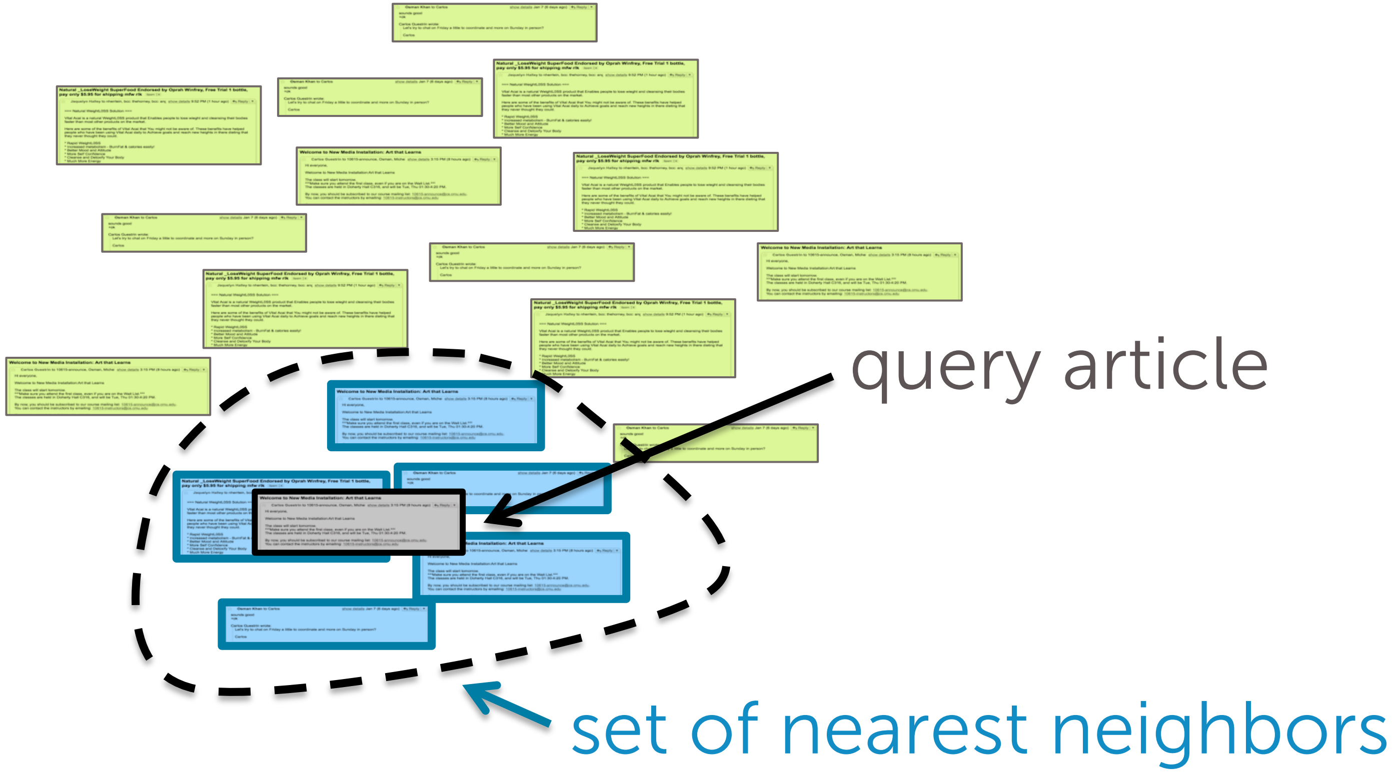
Output $\mathbf{x}^{NN}$:
"nearest" point or
set of points to query

Retrieve "nearest neighbor" article

Space of all articles,
organized by similarity of text

Or set of nearest neighbors

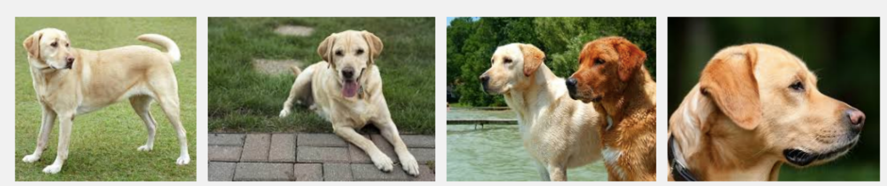
Space of all articles,
organized by similarity of text



Retrieval applications

Just about everything…

Images

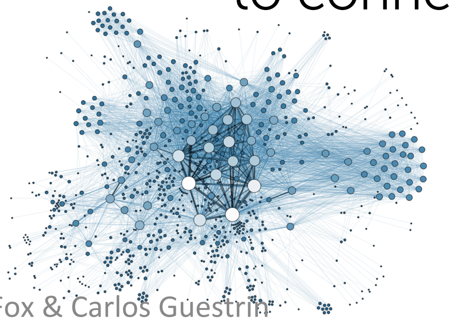


Products

Streaming content:
- Songs
- Movies
- TV shows
- …

News articles

Social networks
(people you might want to connect with)



What is clustering?

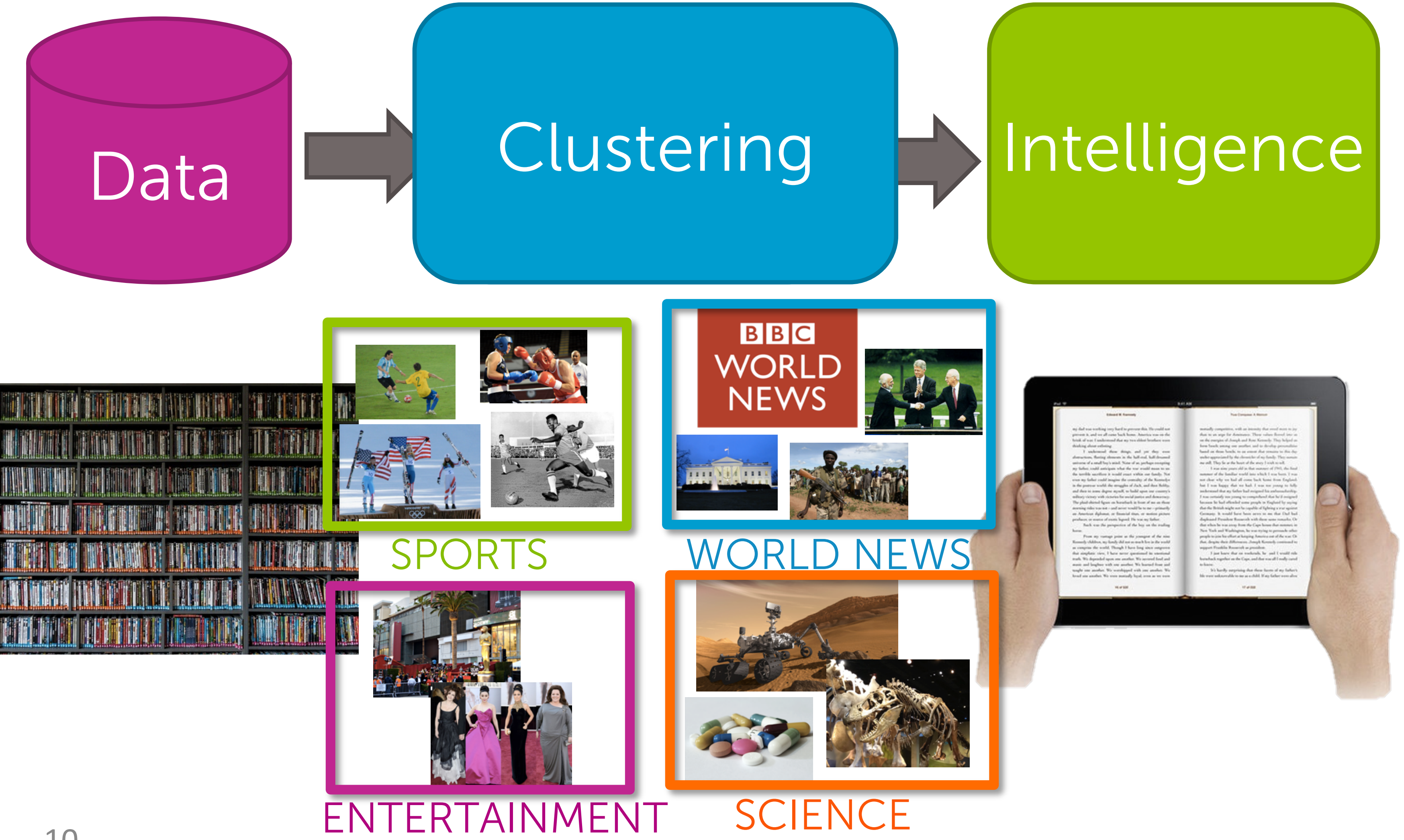
Discover groups of similar inputs

Input {x}:
features for points in dataset

Separate points into disjoint sets

Output {z}:
cluster labels per datapoint

Case Study:
Clustering documents by “topic”

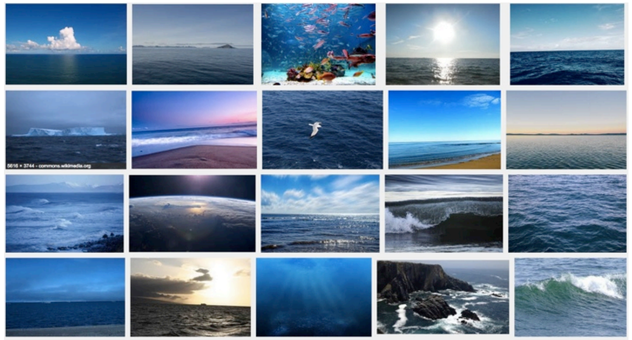


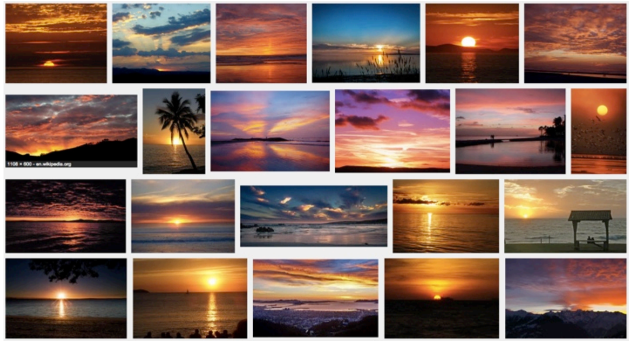
Just like retrieval, clustering has applications almost everywhere

Clustering images

For search, group as:

- Ocean
- Pink flower
- Dog
- Sunset
- Clouds
- …





Or Coursera learners…

Discover groups of learners for better targeting of courses





Impact of retrieval & clustering

Impact of retrieval & clustering

- Foundational ideas
- Lots of information can be extracted using these tools (exploring user interests and interpretable structure relating groups of users based on observed behavior)

Course overview

Course philosophy: **Always use case studies & …**

Core concept

Visual

Algorithm

Practical

Implement

Advanced topics

OPTIONAL

Overview of content

- **Models**
  - Nearest neighbors
  - Clustering
  - Mixture of Gaussians
  - Latent Dirichlet allocation
- **Algorithms**
  - KD-trees
  - Locality sensitive hashing
  - k-means
  - MapReduce
  - Expectation Maximization
  - Gibbs sampling
- **Core ML**
  - Distance metrics
  - Approximation algorithms
  - Unsupervised learning
  - Probabilistic modeling
  - Data parallel problems
  - Bayesian inference

Course outline

Overview of content

Models
- Nearest neighbors
  Module 1
- Clustering
  Module 2, 3
- Mixture of Gaussians
  Module 3
- Latent Dirichlet allocation
  Module 4

Algorithms
- KD-trees
  Module 1
- Locality sensitive hashing
  Module 1
- k-means
  Module 2
- MapReduce
  Module 2
- Expectation Maximization
  Module 3
- Gibbs sampling
  Module 4

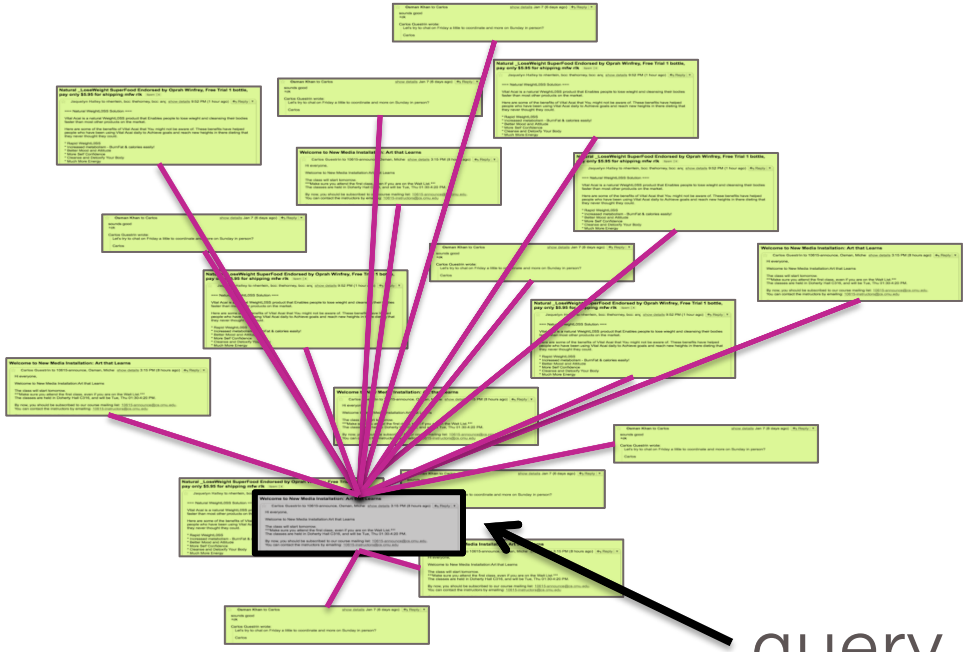
Core ML
- Distance metrics
  Module 1
- Approximation algorithms
  Module 1
- Unsupervised learning
  Module 2
- Probabilistic modeling
  Module 2, 3, 4
- Data parallel problems
  Module 2
- Bayesian inference
  Module 4

Module 1: Nearest neighbor search

Reading doc and want to find related doc

Module 1: Nearest neighbor search

Compute distances to all other documents and return closest



query article

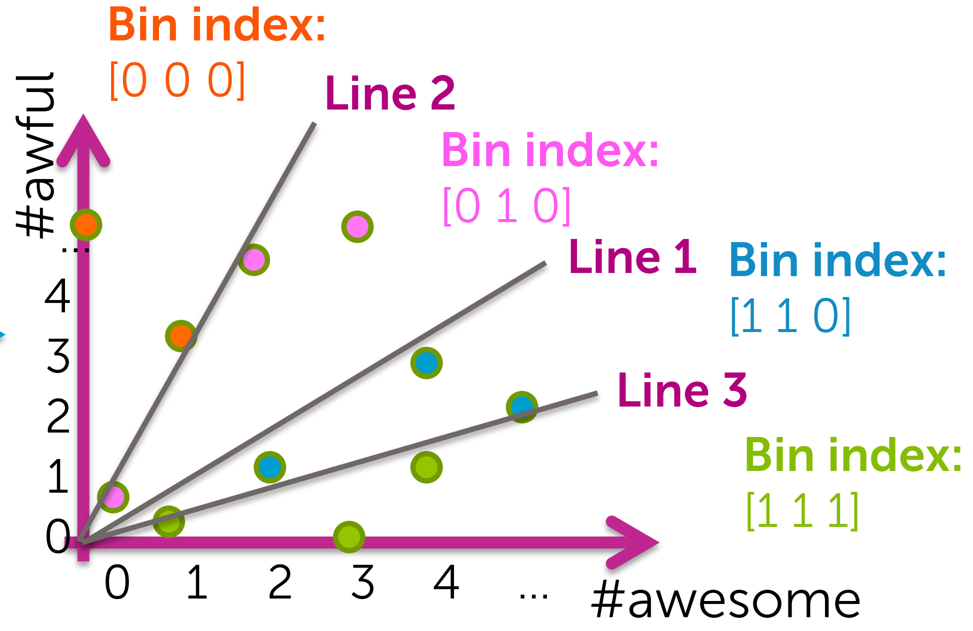
Critical elements:

- Doc representation
- Distance measure

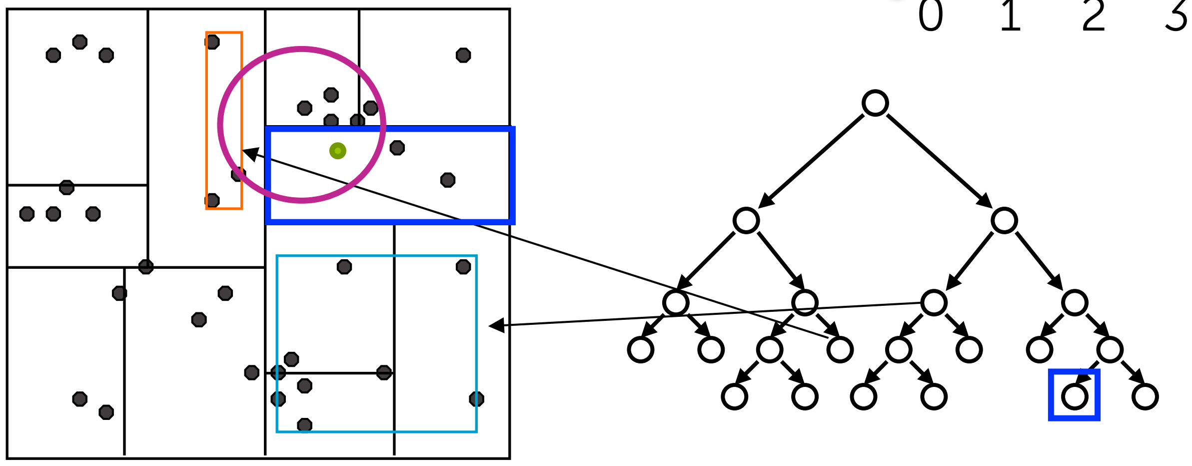
Module 1: Nearest neighbor search

Efficient and approximate NN search

LSH



KD-trees

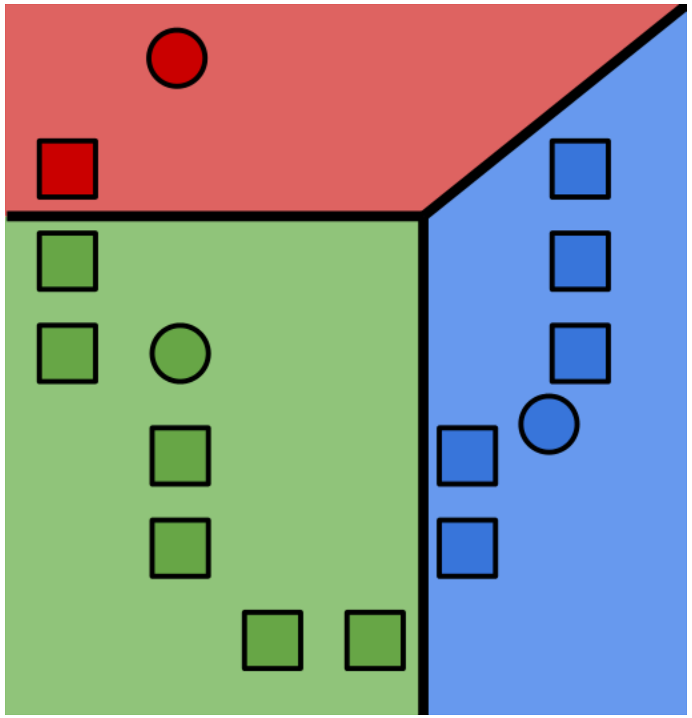


Module 2: k-means and MapReduce

Discover *clusters* of related documents

Module 2: k-means and MapReduce

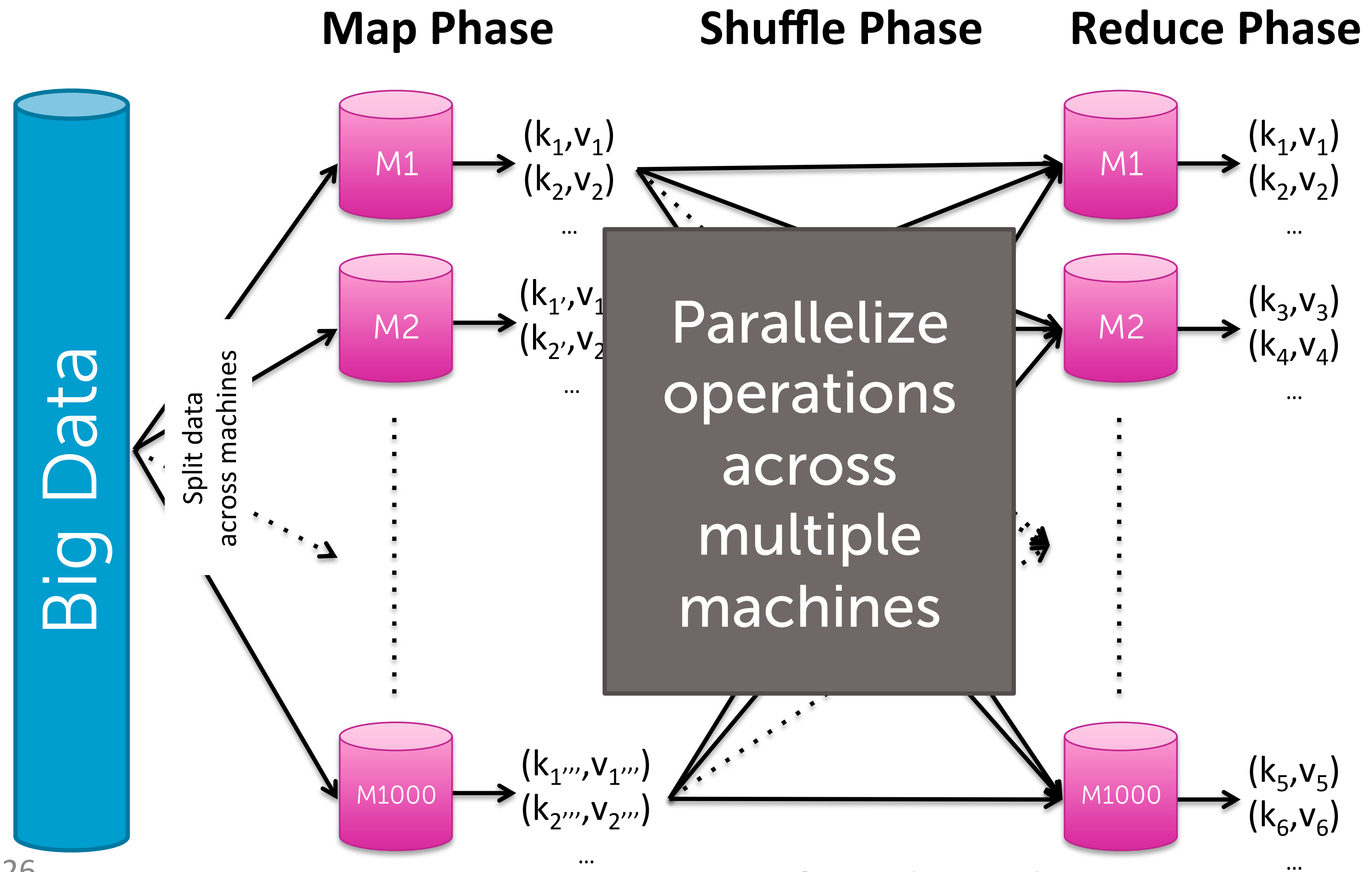
k-means aims to minimize sum of square distances to cluster centers



Makes hard assignments of data points to clusters

Unsupervised learning task

Module 2: k-means and MapReduce



Module 3: Mixture Models

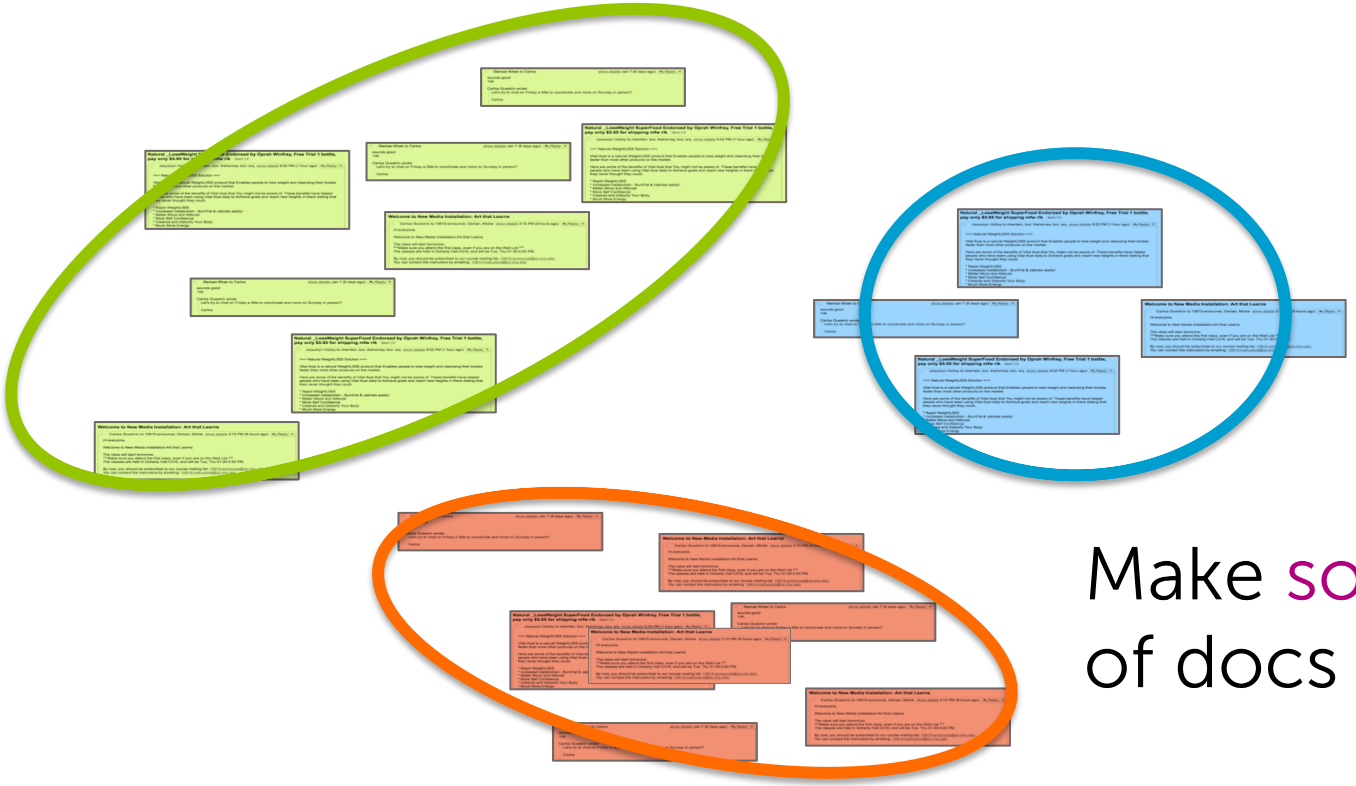
Probabilistic clustering model

captures
uncertainty
in clustering

Module 3: Mixture Models

Module 3: Mixture Models

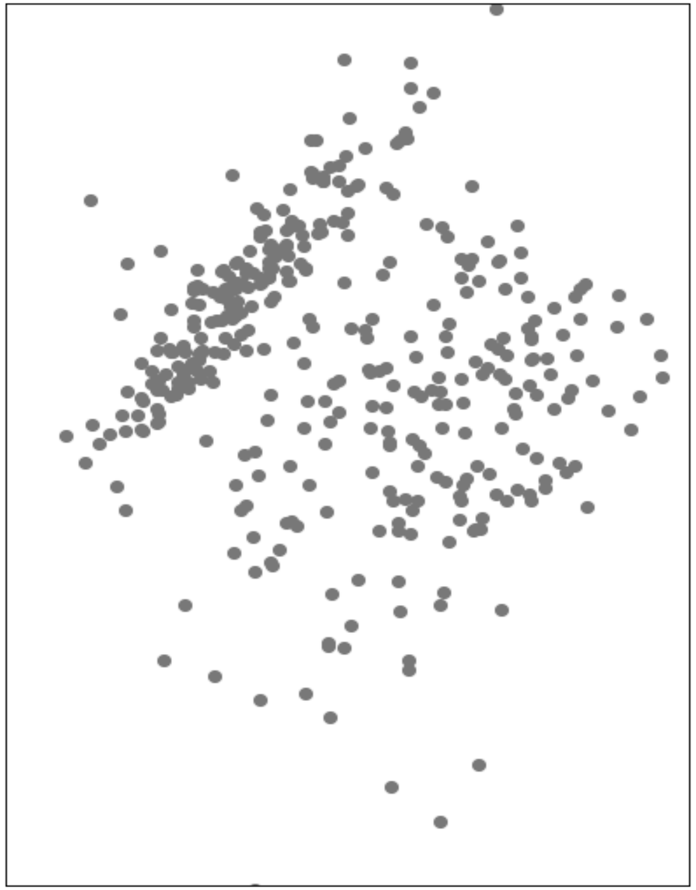
Assignments of docs to clusters based on location *and* shape, not just location



Make soft assignments of docs to each cluster

Module 3: Mixture Models

Data



EM algorithm →
soft assignments

Module 4: Latent Dirichlet Allocation

Modeling the Complex Dynamics and Changing Correlations of Epileptic Events

Drausin F. Wulsin[a], Emily B. Fox[c], Brian Litt[a,b]

[a]Department of Bioengineering, University of Pennsylvania, Philadelphia, PA
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[c]Department of Statistics, University of Washington, Seattle, WA

Abstract

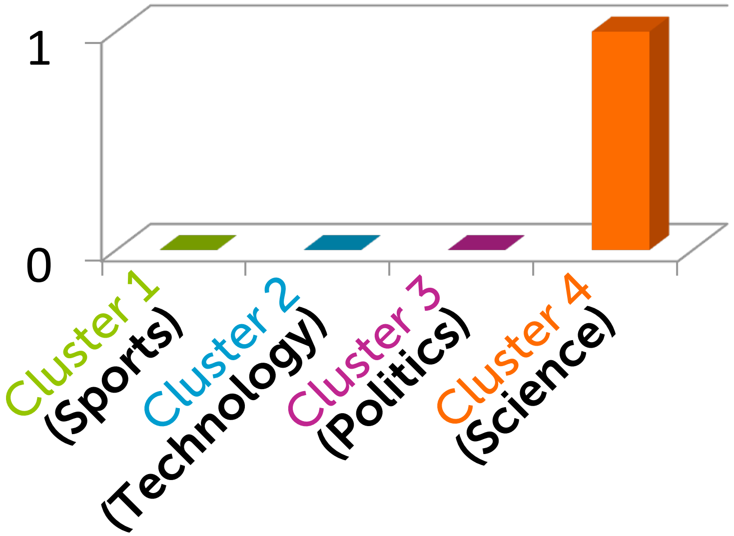
Patients with epilepsy can manifest short, sub-clinical epileptic "bursts" in addition to full-blown clinical seizures. We believe the relationship between these two classes of events—something not previously studied quantitatively—could yield important insights into the nature and intrinsic dynamics of seizures. A goal of our work is to parse these complex epileptic events into distinct dynamic regimes. A challenge posed by the intracranial EEG (iEEG) data we study is the fact that the number and placement of electrodes can vary between patients. We develop a Bayesian nonparametric Markov switching process that allows for (i) shared dynamic regimes between a variable number of channels, (ii) asynchronous regime-switching, and (iii) an unknown dictionary of dynamic regimes. We encode a sparse and changing set of dependencies between the channels using a Markov-switching Gaussian graphical model for the innovations process driving the channel dynamics and demonstrate the importance of this model in parsing and out-of-sample predictions of iEEG data. We show that our model produces intuitive state assignments that can help automate clinical analysis of seizures and enable the comparison of sub-clinical bursts and full clinical seizures.

Keywords: Bayesian nonparametric, EEG, factorial hidden Markov model, graphical model, time series

1. Introduction

Despite over three decades of research, we still have very little idea of what defines a seizure. This ignorance stems both from the complexity of epilepsy as a disease and a paucity of quantitative tools that are flexible

Based on science related words, maybe doc in cluster 4



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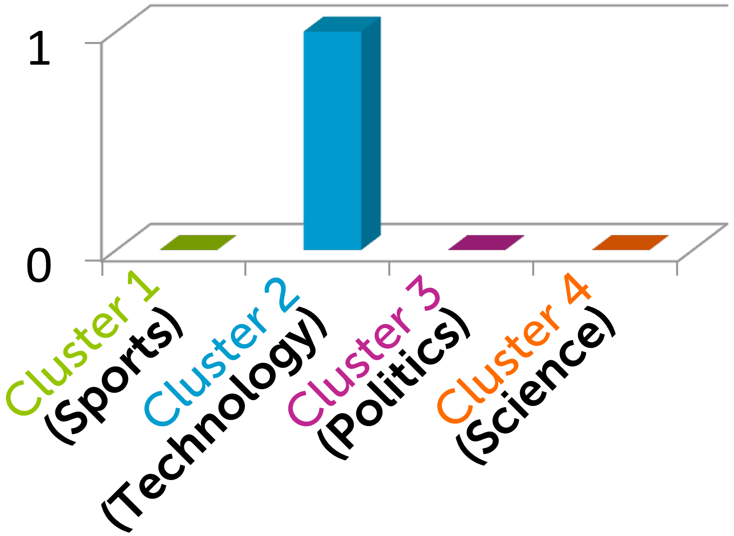
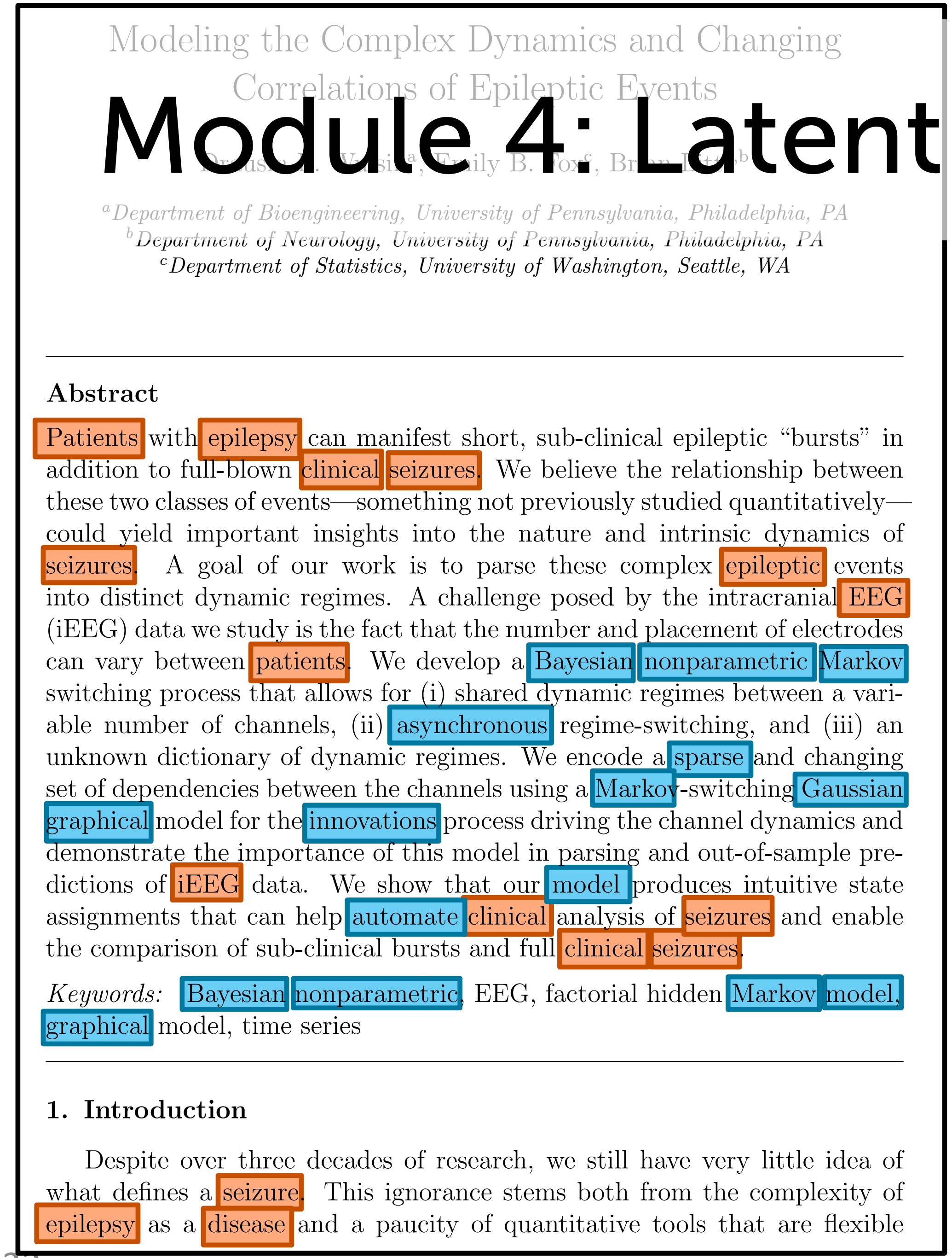
Or maybe cluster 2 (technology) is a better fit



Module 4: Latent Dirichlet Allocation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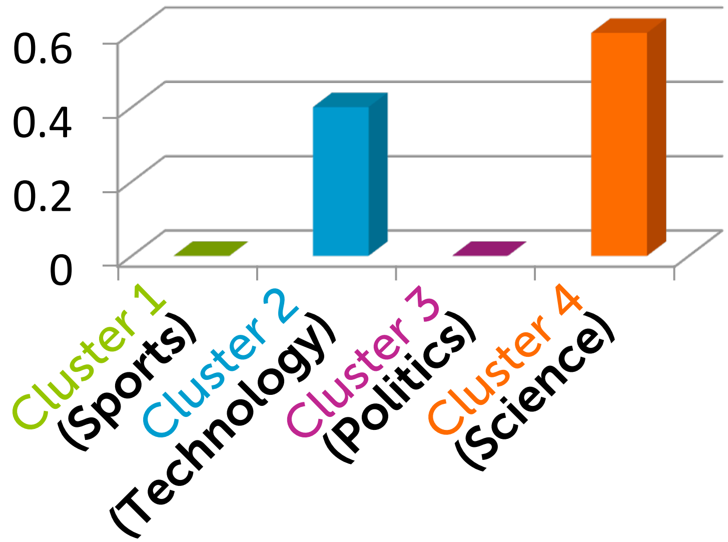
Really, it's about science and technology



Module 4: Latent Dirichlet Allocation

Each cluster/topic defined by probability of words in vocab

SCIENCE	
experiment	0.1
test	0.08
discover	0.05
hypothesize	0.03
climate	0.01
…	…

TECH	
develop	0.18
computer	0.09
processor	0.032
user	0.027
internet	0.02
…	…

SPORTS	
player	0.15
score	0.07
team	0.06
goal	0.03
injury	0.01
…	…

…

Topic vocab distributions:

TOPIC 1	
Word 1	?
Word 2	?
Word 3	?
Word 4	?
Word 5	?
...	...

TOPIC 2	
Word 1	?
Word 2	?
Word 3	?
Word 4	?
Word 5	?
...	...

TOPIC 3	
Word 1	?
Word 2	?
Word 3	?
Word 4	?
Word 5	?
...	...

⋮

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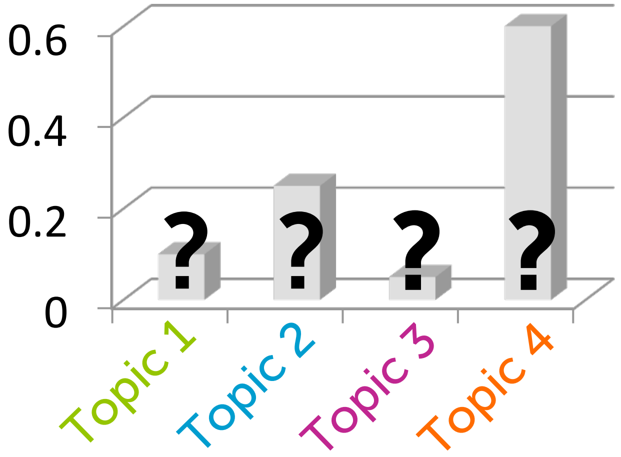
Document topic proportions:



Unsupervised learning task

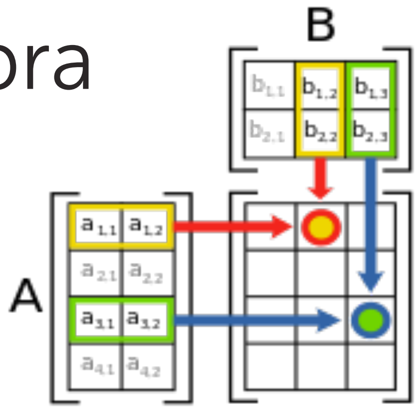
Assumed background

Courses 1, 2, & 3 in this ML Specialization

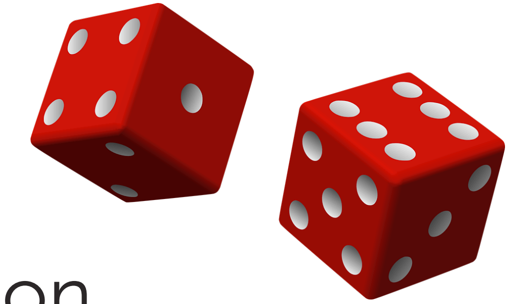
- Course 1: Foundations
  - Overview of ML case studies
  - Black-box view of ML tasks
  - Programming & data manipulation skills
- Course 2: Regression
  - Data representation (input, output, features)
  - Basic statistical concepts: mean/variance
  - Basic ML concepts:
    - ML algorithm
    - Coordinate ascent
    - Overfitting
    - Regularization
- Course 3: Classification
  - Distributions and conditional distributions
  - Maximum likelihood estimation
  - References to:
    - Linear classifier
    - Multiclass classification
    - Boosting

Math background

- Basic linear algebra
  - Vectors
  - Matrices
  - Matrix multiply

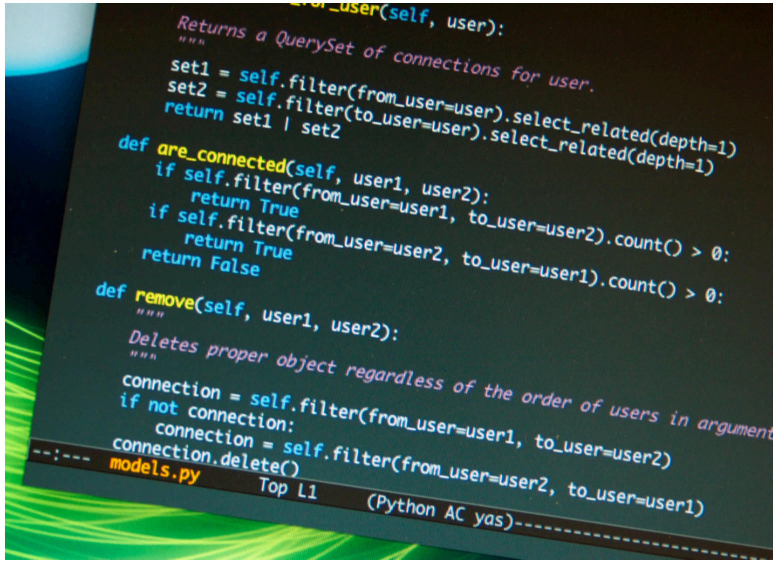


- Basic probability
  - Fundamental laws
  - Distribution and conditional distribution



Programming experience

- Basic Python used
  - Can pick up along the way if knowledge of other language



Reliance on GraphLab Create

- SFrames will be used, though not required
  - open source project of Dato (creators of GraphLab Create)
  - can use pandas and numpy instead
- Assignments will:
  1. Use GraphLab Create to explore high-level concepts
  2. Ask you to implement most algorithms without GraphLab Create

- Net result:
  - learn how to code methods in Python

Computing needs

- Using your own computer:
  - Basic desktop or laptop
    - 64-bit required if using SFrame
  - Access to internet
  - Ability to:
    - Install and run Python (and Numpy, GraphLab Create,…)
    - Store a few GB of data
- Will also provide alternative, pre-configured machine in Cloud

Let's get started!