

CMSC320 Introduction to Data Science: Course Introduction and Overview

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Business First

Course Webpage: <http://bit.ly/hcb-ids>

What is Data Science?

Data science encapsulates the interdisciplinary activities required to create data-centric artifacts and applications that address specific scientific, socio-political, business, or other questions.

Data

Measureable units of information gathered or captured from activity of people, places and things.

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Specific Questions

Seeking to understand a phenomenon, natural, social or other

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Can we formulate specific questions for which an answer posed in terms of patterns observed, tested and or modeled in data is appropriate.

Interdisciplinary Activities

- Formulating a question, assessing the appropriateness of the data and findings used to find an answer require understanding of the specific subject area.

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- Formulating a question, assessing the appropriateness of the data and findings used to find an answer require understanding of the specific subject area.
- Deciding on the appropriateness of models and inferences made from models based on the data at hand requires understanding of statistical and computational methods.

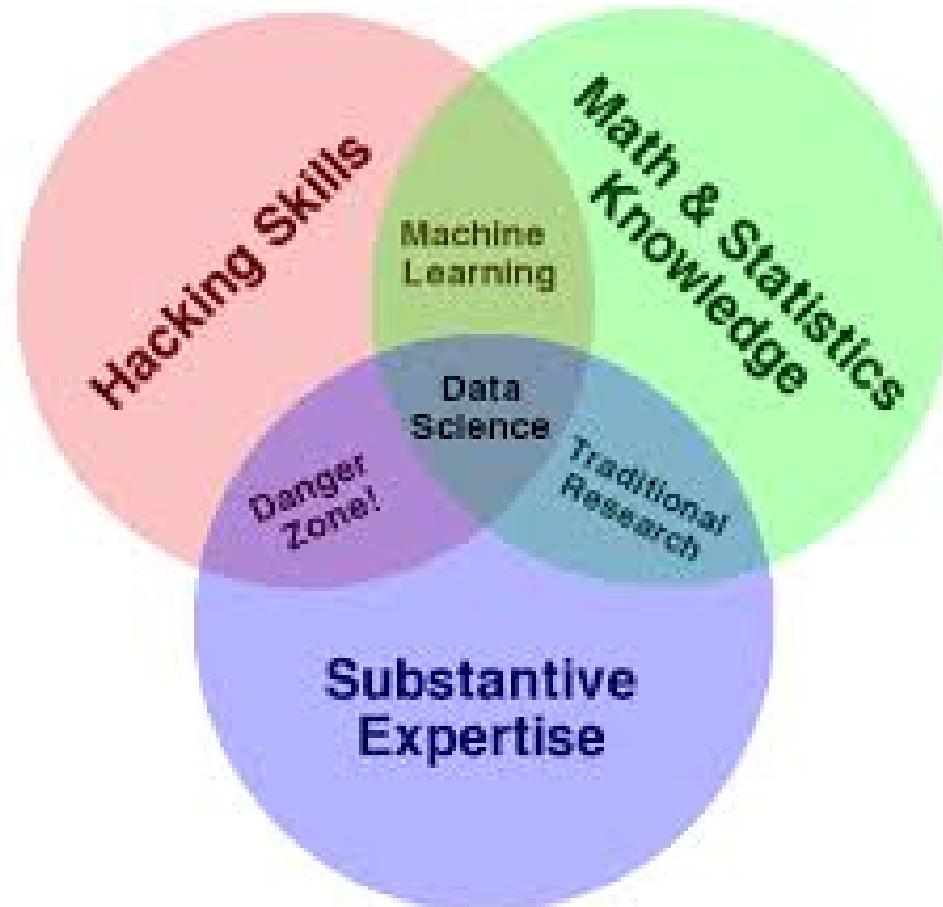
Data-centric artifacts and applications

- Answers to questions derived from data are usually shared and published in meaningful, succinct but sufficient, reproducible artifacts (papers, books, movies, comics).

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- Going a step further, interactive applications that let others explore data, models and inferences are great.

Data Science



Why Data Science?

The granularity, size and accessibility data, comprising both physical, social, commercial and political spheres has exploded in the last decade or more.

I keep saying that the sexy job in the next 10 years will be statisticians”

Hal Varian, Chief Economist at Google

(http://www.nytimes.com/2009/08/06/technology/06stats.html?_r=0)

Why Data Science?

“The ability to take data—to be able to understand it, to process it, to extract value from it, to visualize it, to communicate it—that’s going to be a hugely important skill in the next decades, not only at the professional level but even at the educational level for elementary school kids, for high school kids, for college kids.”

Hal Varian

(http://www.mckinsey.com/insights/innovation/hal_varian_on_how_the_web_

Why Data Science?

“Because now we really do have essentially free and ubiquitous data. So the complimentary scarce factor is the ability to understand that data and extract value from it.”

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Data Science in Society

Large amounts of data produced across many spheres of human activity,

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Many societal questions may be addressed by characterizing patterns in data.

Data Science in Society

This can range from unproblematic questions:

- how to dissect a large creative corpora, say music, literature, based on raw characteristics of those works, text, sound and image.

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To more problematic questions

- analysis of intent, understanding, appreciation and valuation of these creative corpora.

Data Science in Society

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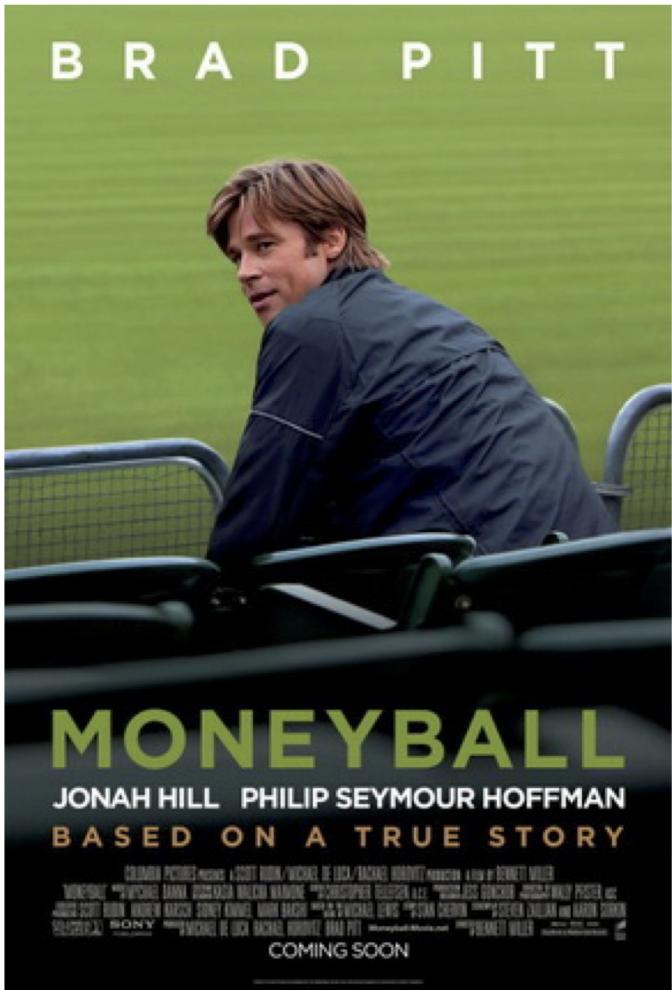
- Is data collected representative of population for which inferences are drawn?
- Are methods employed learning latent unfair factors from ostensibly fair data?
- These are issues that the research community is now starting to address.

Data Science in Society

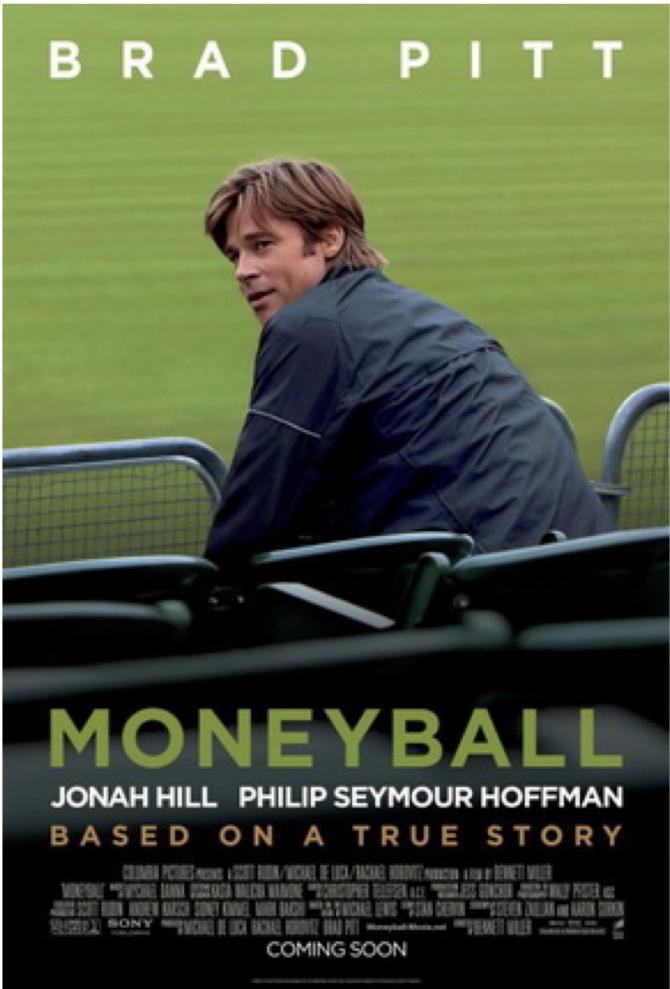
In all settings, issues of ethical collection of data, application of models, and deployment of data-centric artifacts are essential to grapple with.

Issues of privacy are equally important.

Data Science in Society



Data Science in Society



Actual

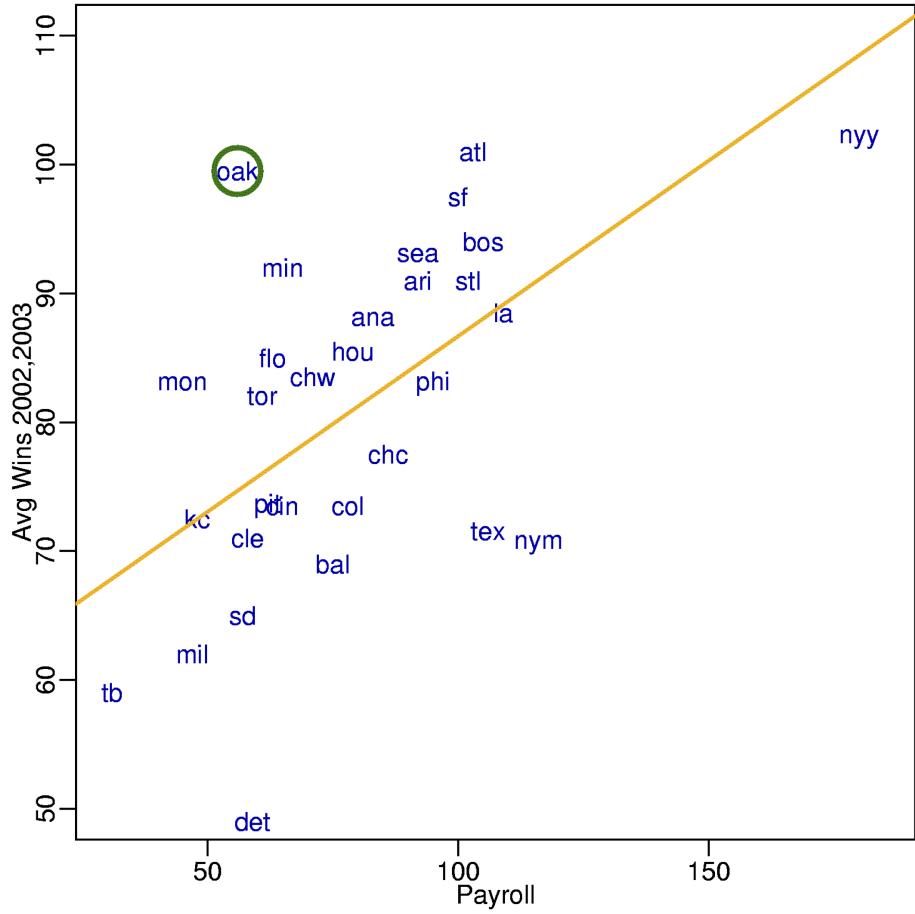


Hollywood



Data Science in Society

In the early 2000's the Oakland A's were winning as much as teams with much bigger payrolls by evaluating players using data differently than other teams.



Data Science in Society

Data Journalism

<http://fivethirtyeight.com>

The screenshot shows the homepage of FiveThirtyEight. At the top left is the site's logo, "FiveThirtyEight". To the right are navigation links for Politics, Sports, Science & Health, Economics, and Culture. On the far right are search and ESPN logos. The main content area features a large image of Donald Trump's face on a grid background. Below the image is a headline: "THE LATEST JAN. 26 The Rockets Love Launching 3s From Way Past The Line". To the right, there's a section titled "INTERACTIVES" with a chart titled "How Popular Is Donald Trump?", last updated 2 days ago, showing a trend line ending at 56.2% Disapprove.

FiveThirtyEight

Politics Sports Science & Health Economics Culture

NBA Podcast: Where Did Jason Kidd Go Wrong?

THE LATEST

JAN. 26

The Rockets Love Launching 3s From Way Past The Line

INTERACTIVES

JAN. 26

How Popular Is Donald Trump?

UPDATED 2 DAYS AGO

56.2%

Disapprove

16 / 50

Data Science in Society

Data Journalism

<http://www.nytimes.com/section/upshot>

Data Science in Society

The story of the Netflix Prize

In October 2006 Netflix announced a prize around their movie recommendation engine.

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Supervised Machine Learning (ML) task:

- Dataset of users and their ratings, (1,2,3,4 or 5 stars), of movies they have rated.
- Build an ML model that given predicts a specific user's rating to a movie they have not rated.

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They can recommend movies to users if they predict high rating.

Data Science in Society

Netflix would award \$1M for the first ML system that provided a 10% improvement to their existing system

Data Science in Society

Existing system had
a 0.9514 mean
squared error



Leaderboard

| Team Name | Best Score | % Improvement |
|---|------------|---------------|
| No Grand Prize candidates yet | -- | -- |
| <u>Grand Prize - RMSE <= 0.8563</u> | | |
| How low can he go? | 0.9046 | 4.92 |
| ML@UToronto A | 0.9046 | 4.92 |
| ssorkin | 0.9089 | 4.47 |
| wxyzconsulting.com | 0.9103 | 4.32 |
| The Thought Gang | 0.9113 | 4.21 |
| NIPS Reject | 0.9118 | 4.16 |
| simonfunk | 0.9145 | 3.88 |
| Bozo_The_Clown | 0.9177 | 3.54 |

Data Science in Society

Within three weeks,
at least 40 teams had
improved upon the
existing Netflix
system.

The top teams were
showing
improvement over
5%.



Leaderboard

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Data Science in Society

Machine Learning

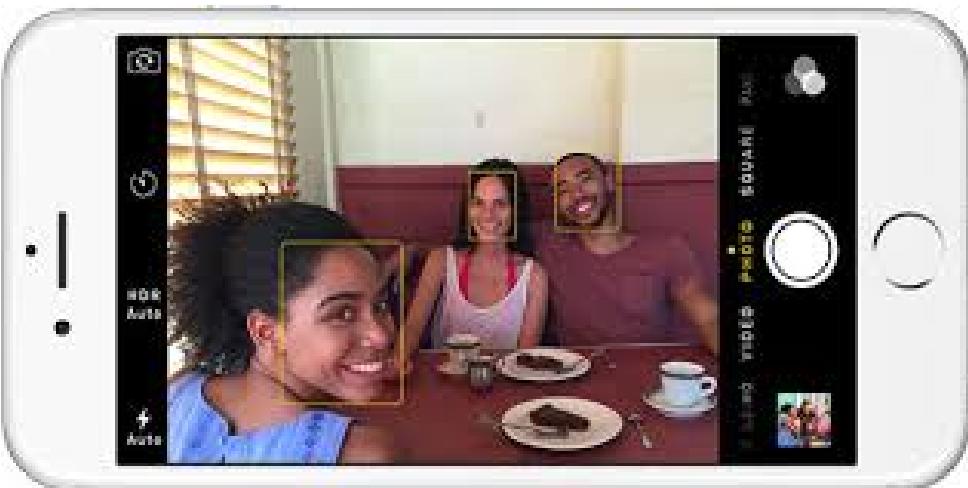
Self driving cars make use of ML models for sensor processing.



Data Science in Society

Machine Learning

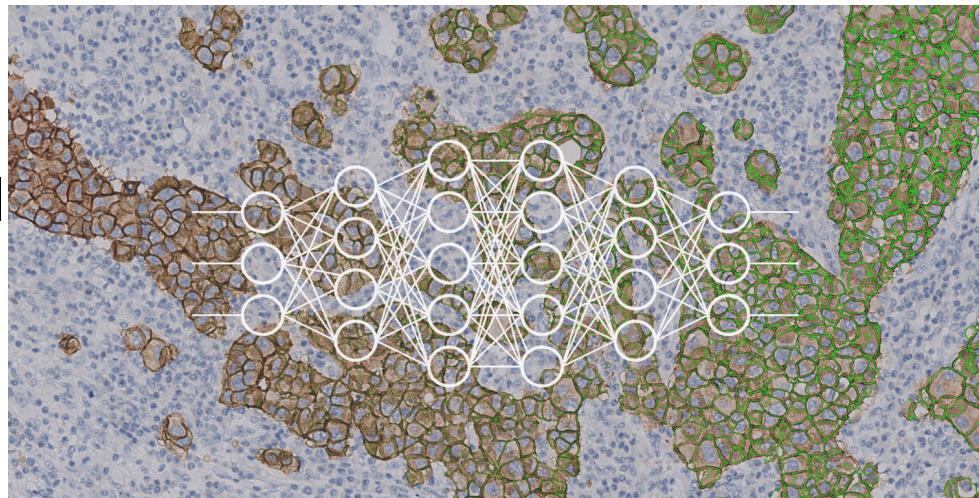
Image recognition software uses ML to identify individuals in photos.



Data Science in Society

Machine Learning

ML models have been applied to medical imaging to yield expert-level prognosis.



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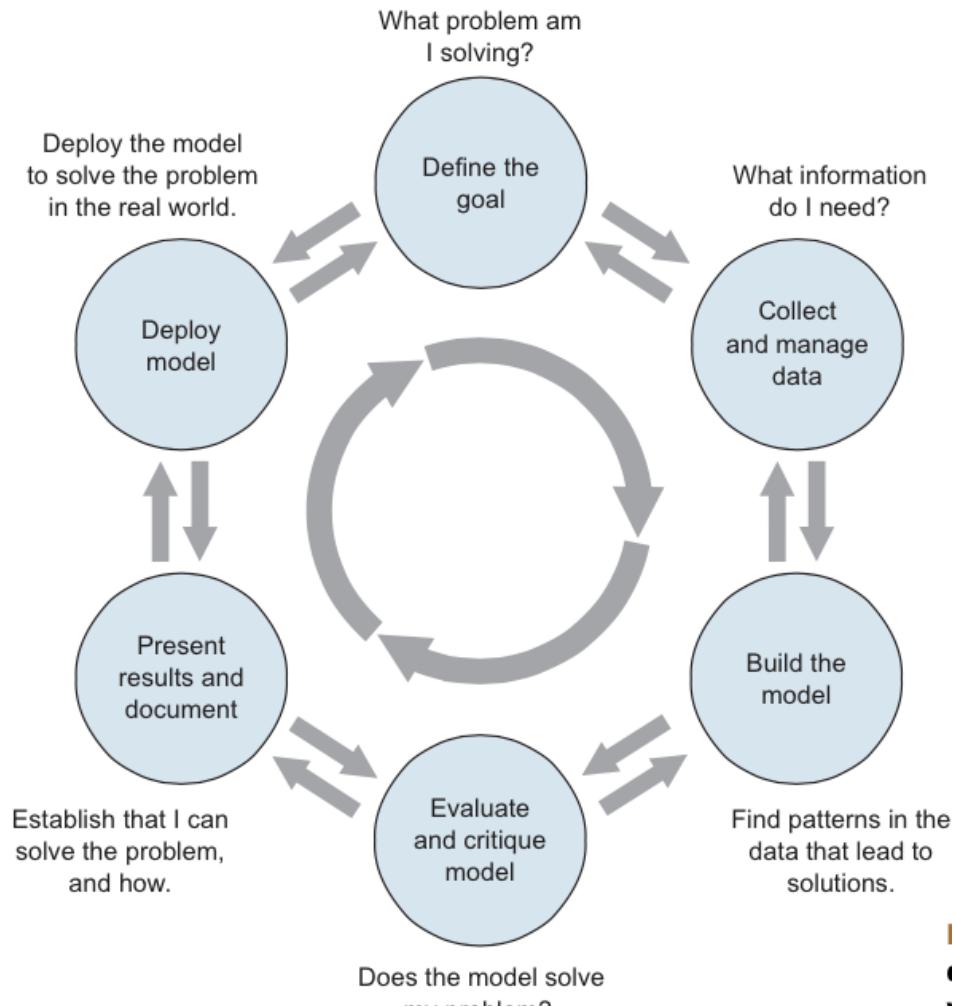
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- Area 3: Modeling
- Area 4: Applications
- Area 5: Communication

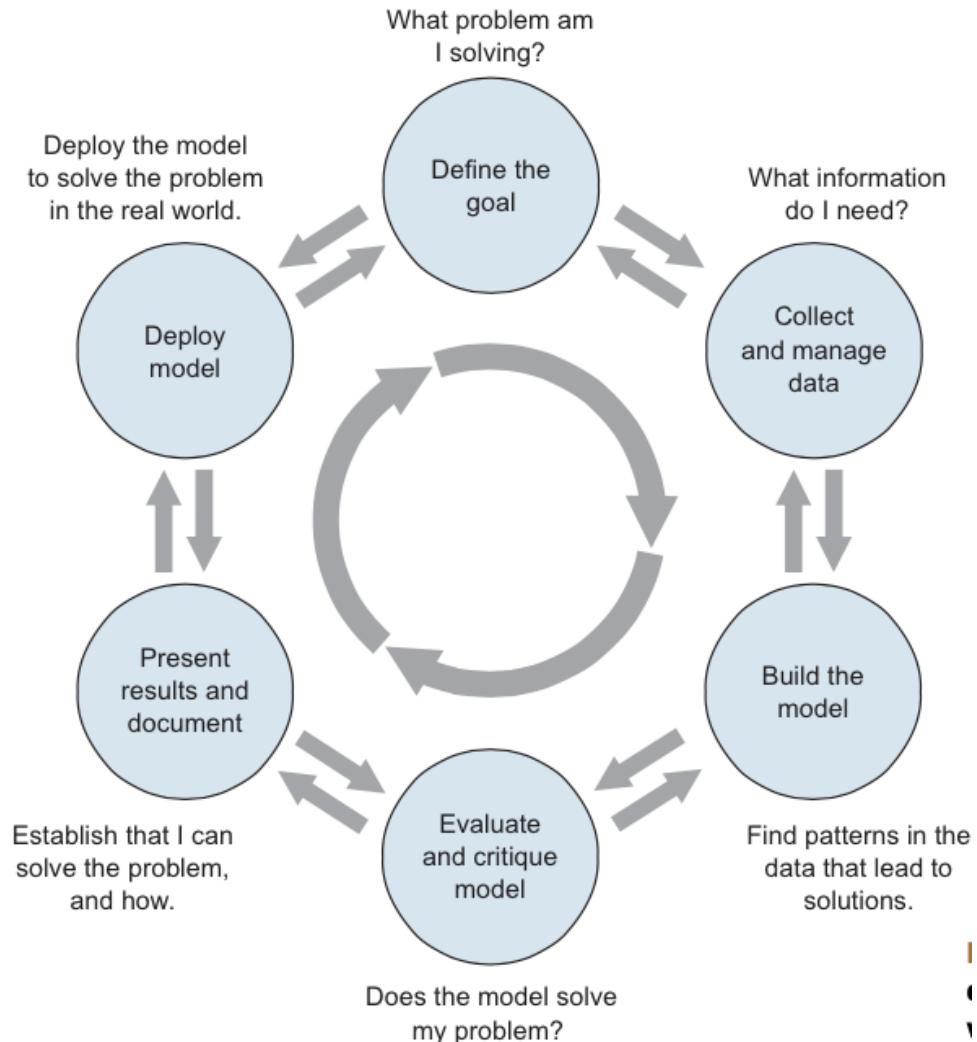
General Workflow

Zumel and Mount



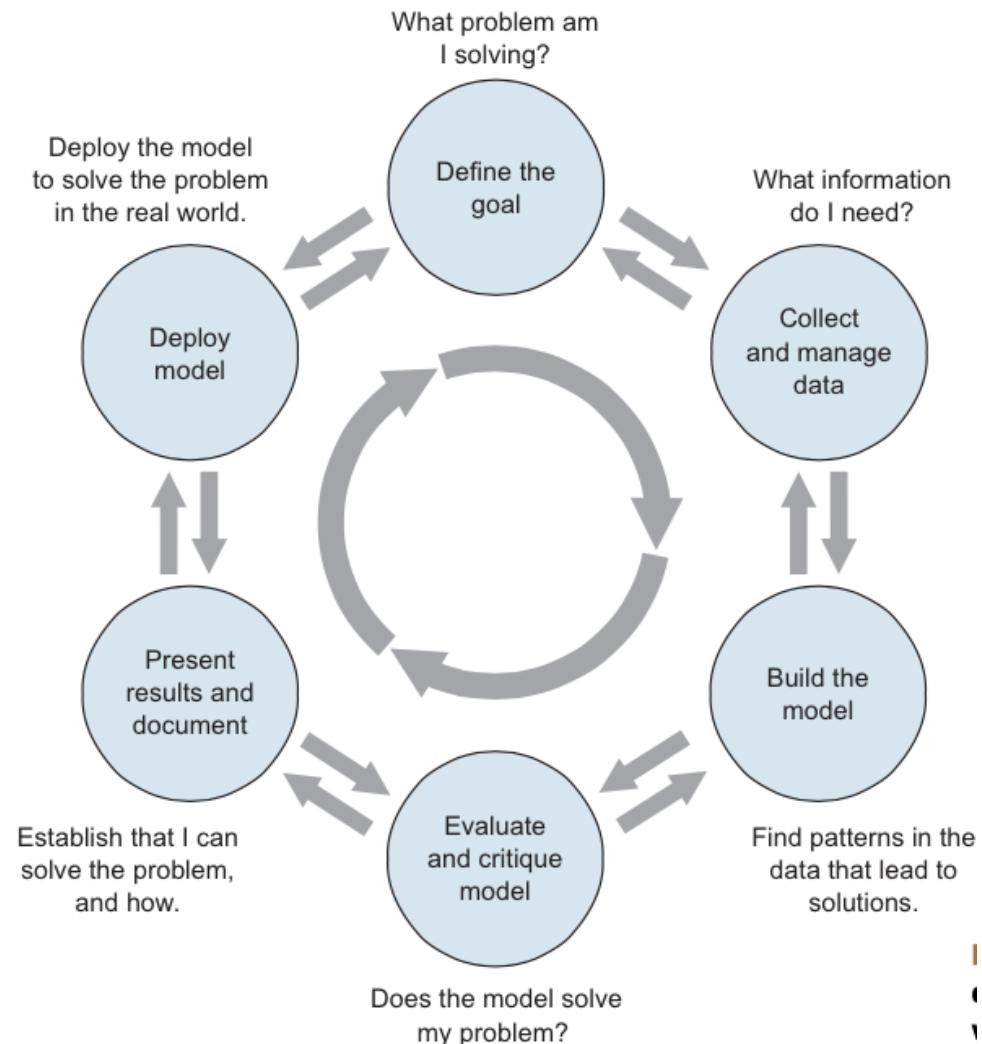
Defining the goal

- What is the question/problem?
- Who wants to answer/solve it?
- What do they know/do now?
- How well can we expect to answer/solve it?
- How well do they want us to answer/solve it?



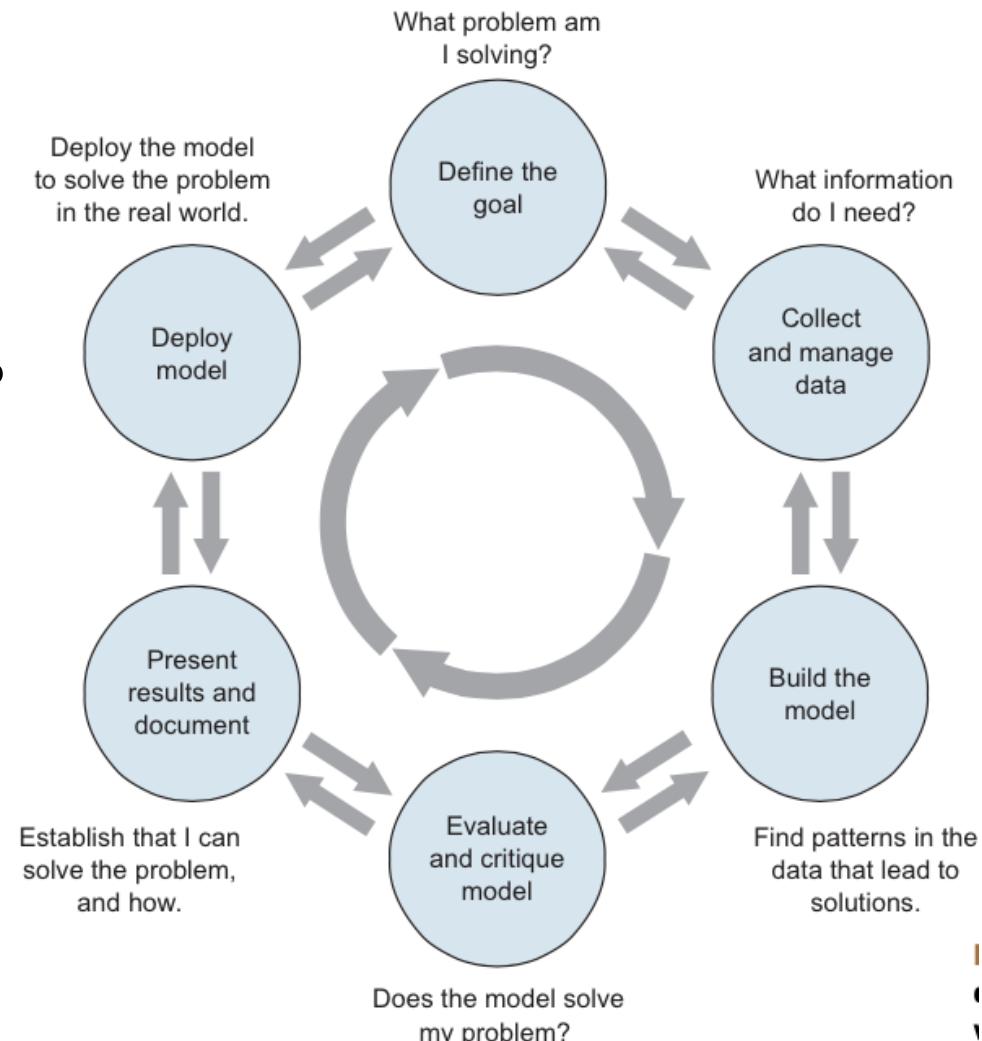
Data collection and Management

- What data is available?
- Is it good enough?
- Is it enough?
- What are sensible measurements to derive from this data? Units, transformations, rates, ratios, etc.



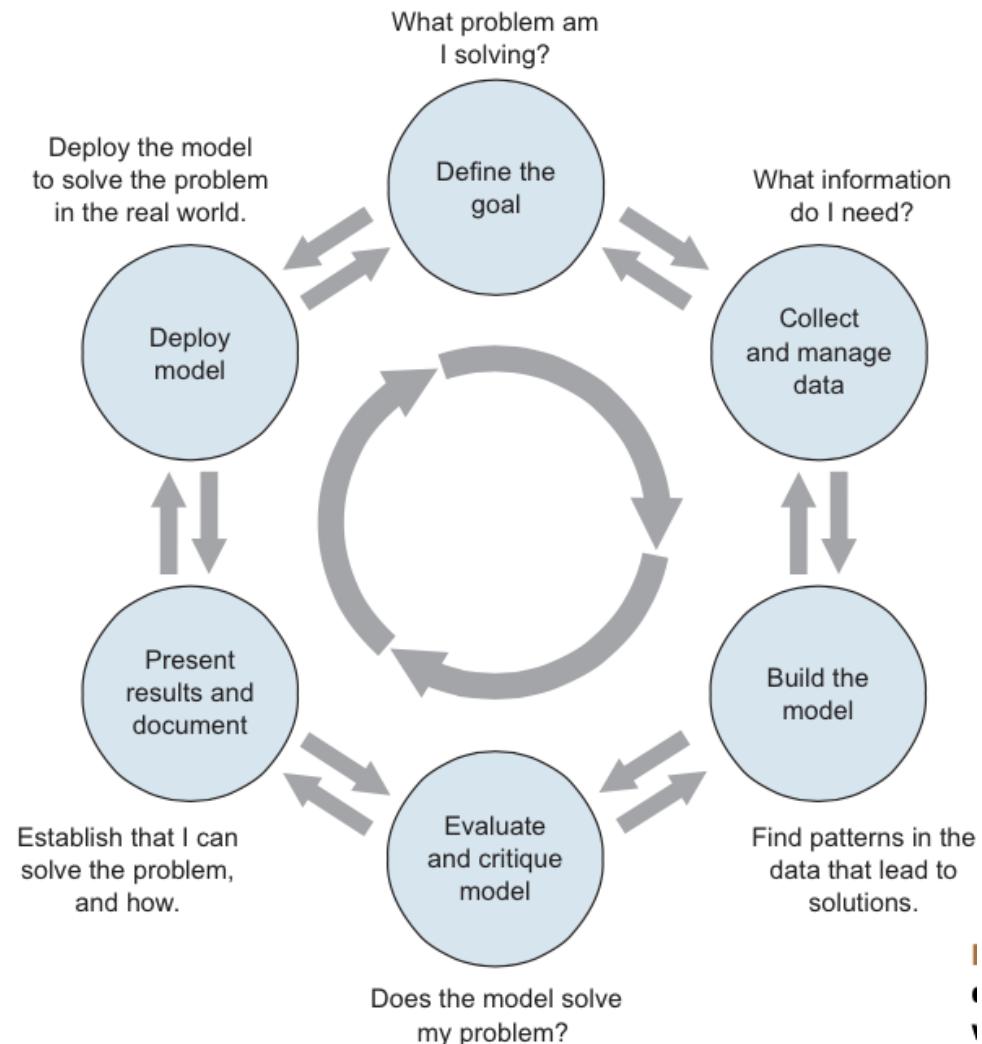
Modeling

- What kind of problem is it? E.g., classification, clustering, regression, etc.
- What kind of model should I use?
- Do I have enough data for it?
- Does it really answer the question?



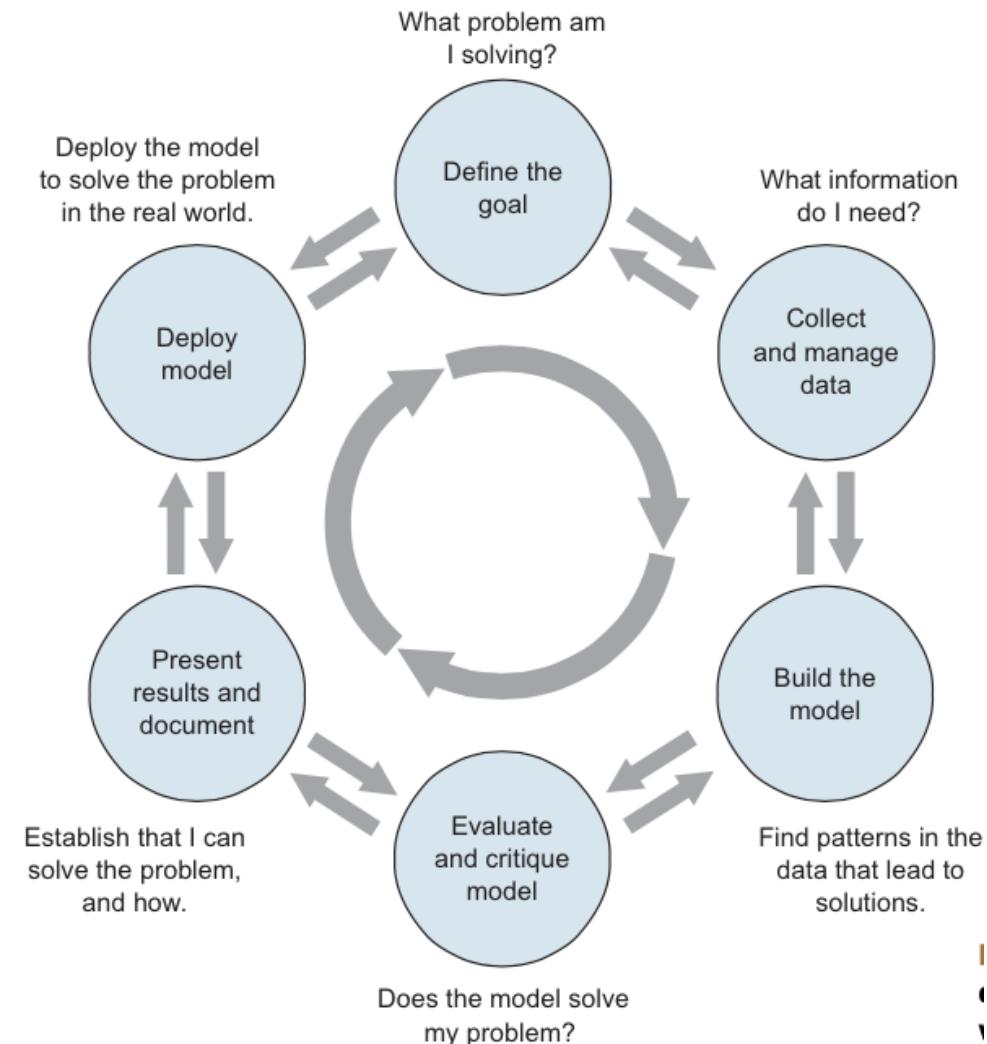
Model evaluation

- Did it work? How well?
- Can I interpret the model?
- What have I learned?



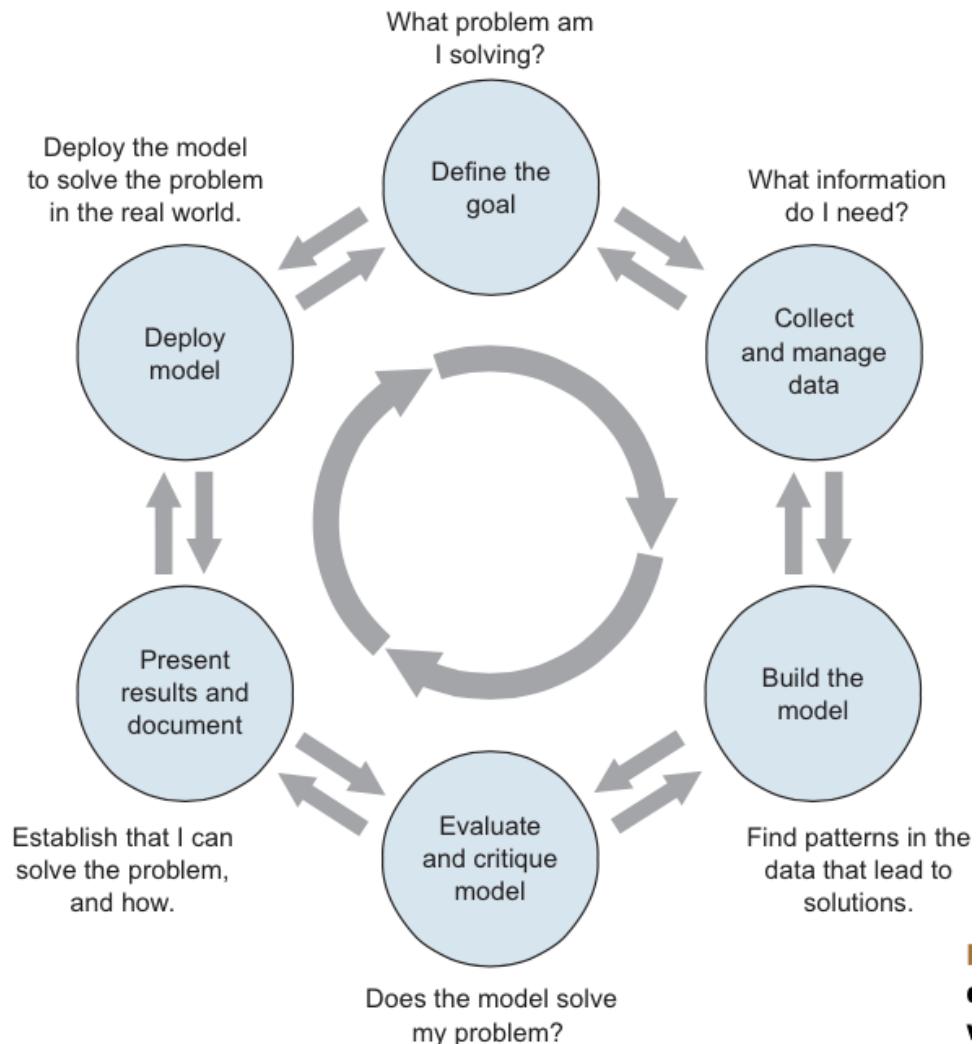
Presentation

- Again, what are the measurements that tell the real story?
- How can I describe and visualize them effectively?



Deployment

- Where will it be hosted?
- Who will use it?
- Who will maintain it?



An Illustrative Analysis

<http://fivethirtyeight.com> has a clever series of articles on the types of movies different actors make in their careers:

<https://fivethirtyeight.com/tag/hollywood-taxonomy/>

I'd like to do a similar analysis. Let's do this in order:

- 1) Let's do this analysis for Diego Luna
- 2) Let's use a clustering algorithm to determine the different types of movies they make
- 3) Then, let's write an application that performs this analysis for any actor and test it with Gael García Bernal

Gathering data

Movie ratings

For this analysis we need to get the movies Diego Luna was in, along with their Rotten Tomatoes ratings. For that we scrape this webpage:

https://www.rottentomatoes.com/celebrity/diego_luna.

| RATING | TITLE | CREDIT | BOX OFFICE | YEAR |
|--------|------------------------------|-----------------------|------------|------|
| 85 | Rogue One: A Star Wars Story | Captain Cassian Andor | \$532.2M | 2016 |
| 89 | Blood Father | Jonah | — | 2016 |

Movie budgets and revenue

For the movie budgets and revenue data we scrape this webpage:

<http://www.the-numbers.com/movie/budgets/all>

This is part of what we have for that table after scraping and cleaning up:

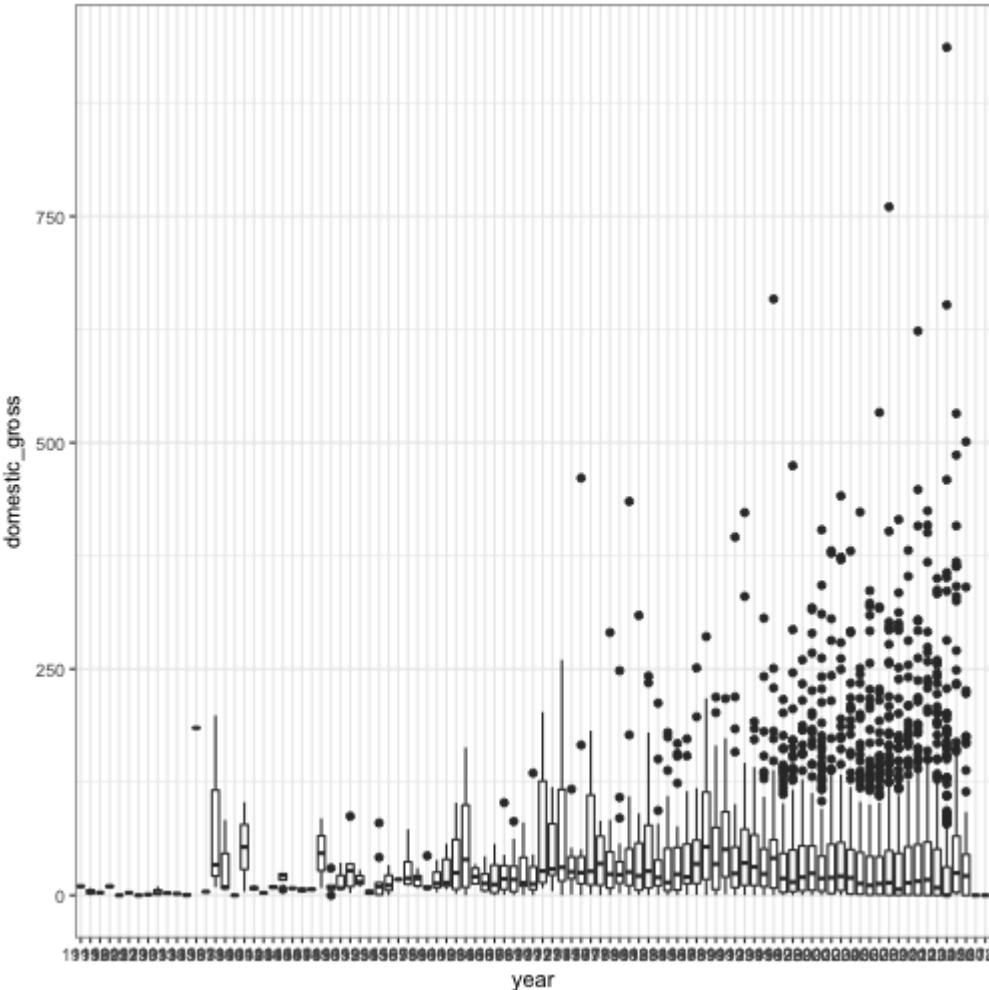
| release_date | movie | production_budget | domestic_gross | worldwide_gross |
|--------------|--|-------------------|----------------|-----------------|
| 2009-12-18 | Avatar | 425 | 760.50762 | 2783.00000 |
| 2015-12-18 | Star Wars Ep. VII: The Force Awakens | 306 | 936.66223 | 2058.00000 |
| | Pirates of the Caribbean: Dead Man's Chest | 165 | 1023.00000 | 2058.00000 |

Movie budgets and revenue

Now we have data for 5363 movies, including its release date, title, production budget, US domestic and worldwide gross earnings. The latter three are in millions of U.S. dollars.

Movie budgets and revenue

One thing we might want to check is if the budget and gross entries in this table are inflation adjusted or not.



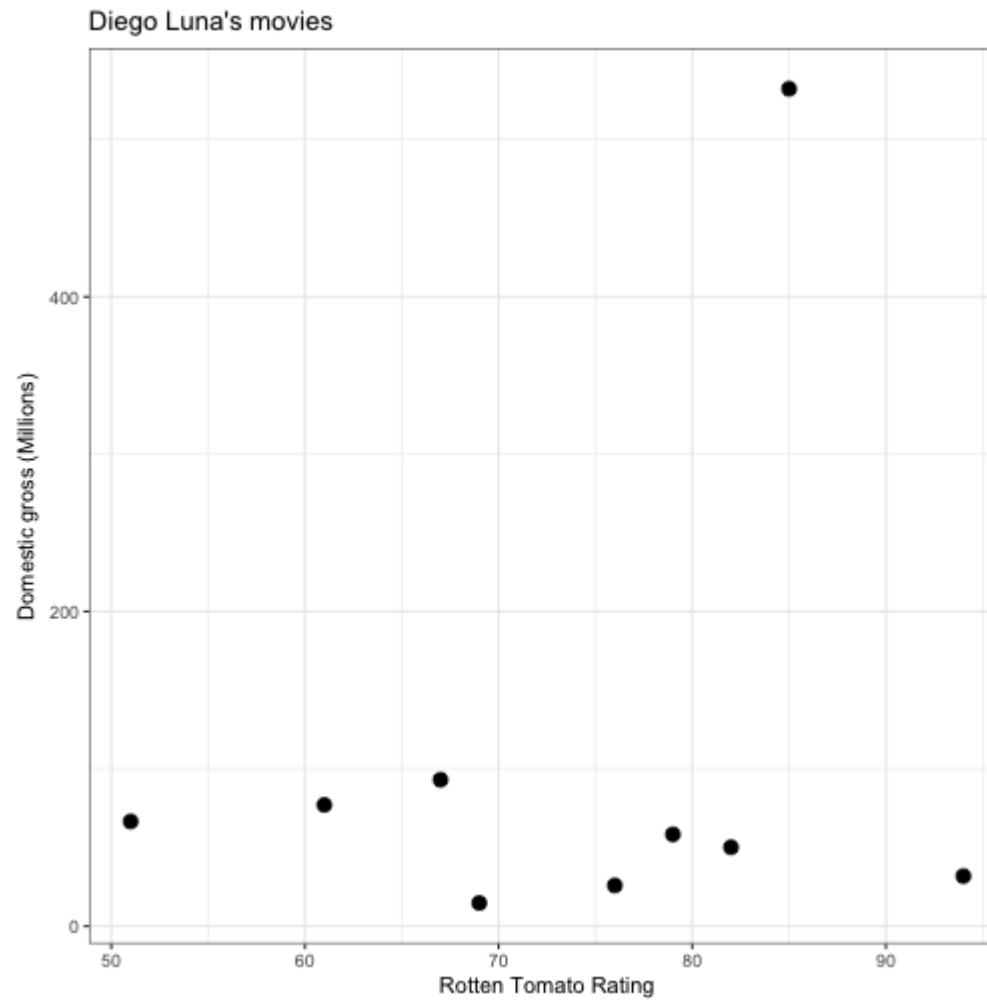
Manipulating the data

Next, we combine the datasets we obtained to get closer to the data we need to make the plot we want.

We combine the two datasets using the movie title, so that the end result has the information in both tables for each movie.

| RATING | TITLE | CREDIT | BOX OFFICE | YEAR | release_date | production_bud |
|--------|------------------------------|-----------------------|---------------|------|--------------|----------------|
| | Rogue One: A Star Wars Story | Captain Cassian Andor | \$532.2M | 2016 | 2016-12-16 | 2016 |
| | The Book | | | | | |

Visualizing the data

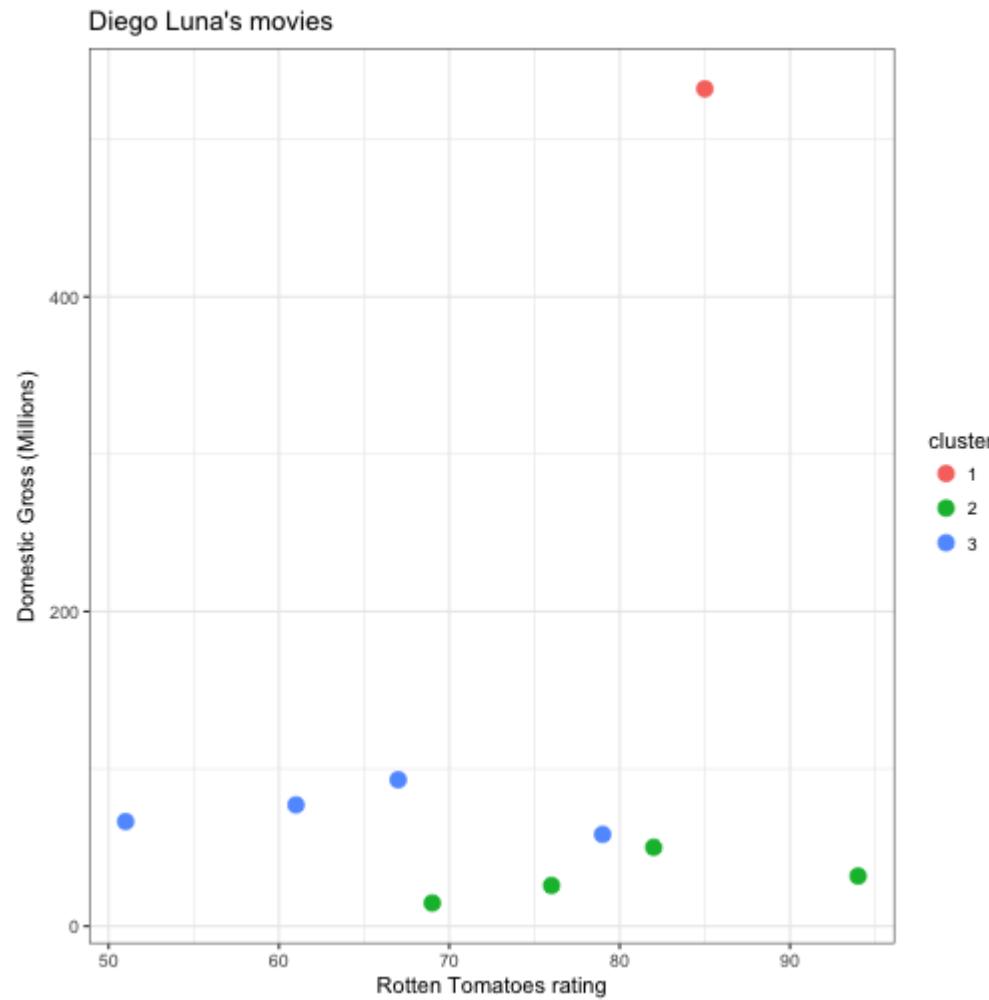


Modeling data

Use a clustering algorithm to partition Diego Luna's movies based on rating and domestic gross.

| TITLE | RATING | domestic_gross | cluster |
|------------------------------|--------|----------------|---------|
| Rogue One: A Star Wars Story | 85 | 532.17732 | 1 |
| The Book of Life | 82 | 50.15154 | 2 |
| Milk | 94 | 31.84130 | 2 |
| Criminal | 69 | 14.70870 | 2 |
| Frida | 76 | 25.88500 | 2 |
| Elysium | 67 | 93.05012 | 3 |

Visualizing model result



Visualizing model result

To make the plot and clustering more interpretable, let's annotate the graph with some movie titles.

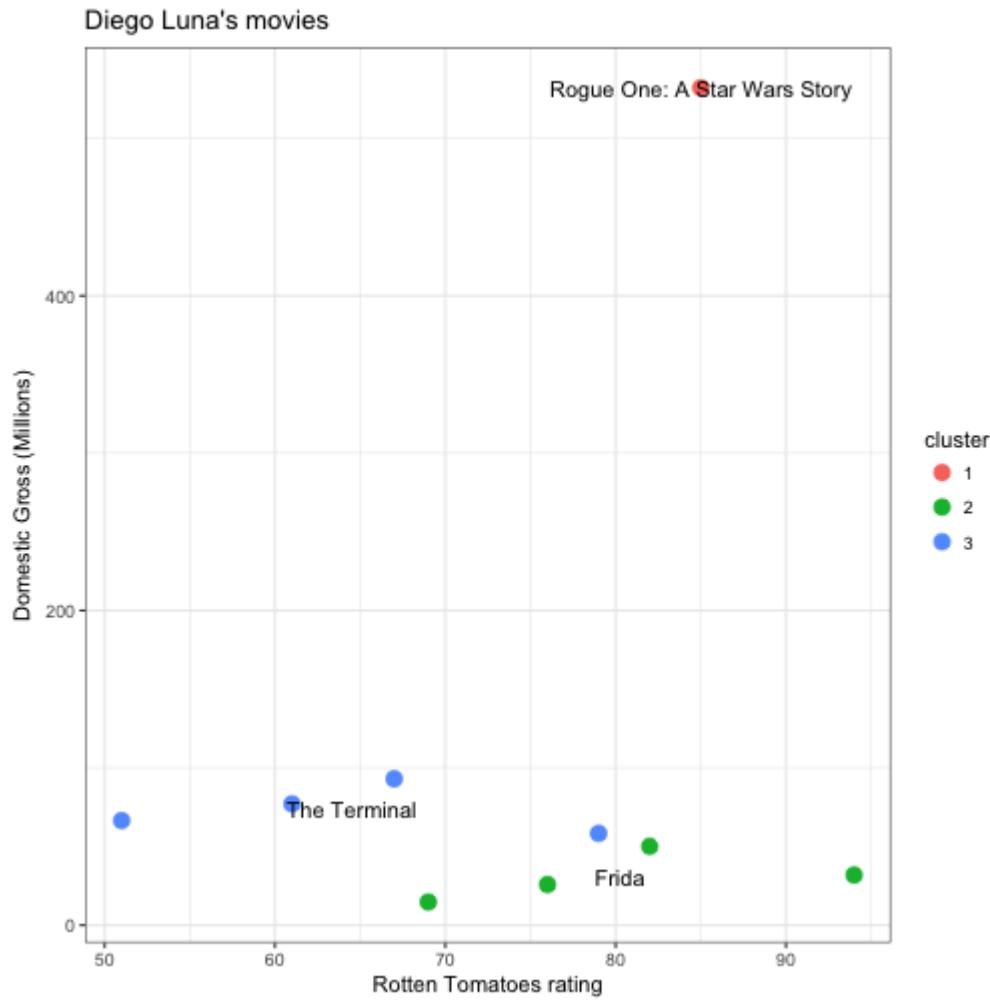
- In the k-means algorithm, each group of movies is represented by an average rating and an average domestic gross.

Visualizing model result

To make the plot and clustering more interpretable, let's annotate the graph with some movie titles.

- In the k-means algorithm, each group of movies is represented by an average rating and an average domestic gross.
- Find the movie in each group that is closest to the average and use that movie title to annotate each group in the plot.

Visualizing model result



Abstracting the analysis

While not a tremendous success, we decide we want to carry on with this analysis. We would like to do this for other actors' movies.

One of the big advantages of using R is that we can write a piece of code that takes an actor's name as input, and reproduces the steps of this analysis for that actor.

We call these *functions*, we'll see them and use them a lot in this course.

Abstracting the analysis

For our analysis, this function must do the following:

1. Scrape movie ratings from Rotten Tomatoes
2. Clean up the scraped data
3. Join with the budget data we downloaded previously
4. Perform the clustering algorithm
5. Make the final plot

With this in mind, we can write functions for each of these steps, and then make one final function that puts all of these together.

Abstracting the analysis

For instance, let's write the scraping function. It will take an actor's name and output the scraped data.

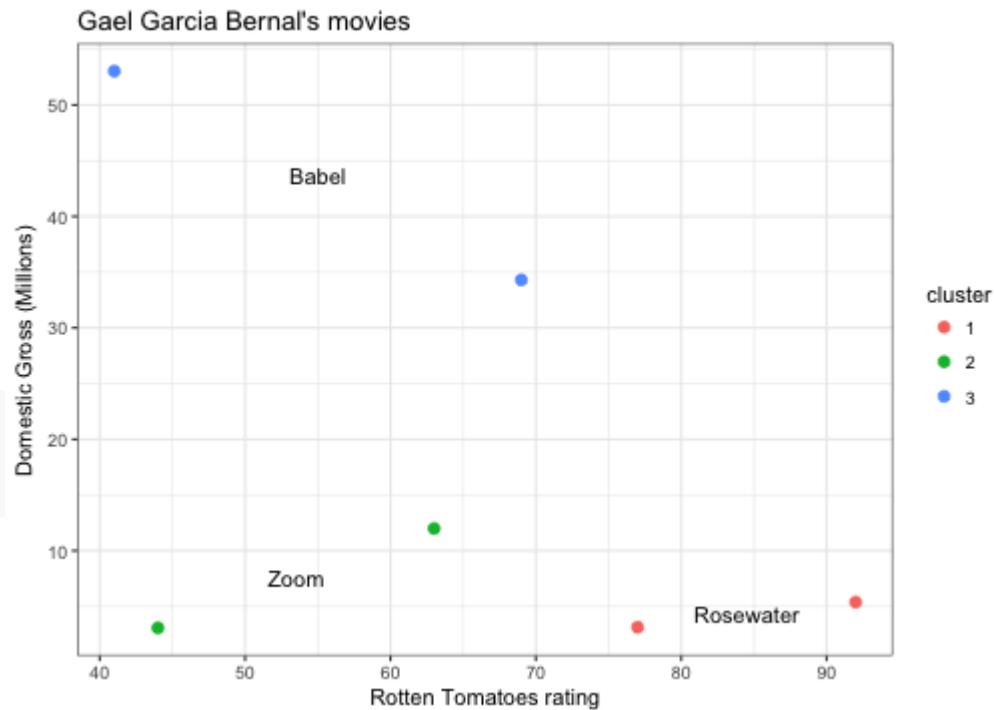
Let's test it with Gael García Bernal:

| RATING | TITLE | CREDIT | BOX OFFICE | YEAR |
|--------------|---------------------------|-----------------|------------|--------------|
| No Score Yet | Viva - A vida é uma festa | Hector | — | 2017 |
| 97% | Coco | Hector | \$192M | 2017 |
| 31% | Salt and Fire | Dr. Fabio Goyan | — | 2017 46 / 50 |

Abstracting the analysis

We can then write functions for each of the steps we did with Diego Luna before.

```
analyze_actor("Gael Garcia Bernal")
```



Making analyses accessible

Now that we have written a function to analyze an actor's movies, we can make these analyses easier to produce by creating an interactive application that wraps our new function. The shiny R package makes creating this type of application easy.

https://hcorrada.shinyapps.io/movie_app/

Summary

In this analysis we saw examples of the common steps and operations in a data analysis:

- 1) Data ingestion: we scraped and cleaned data from publicly accessible sites
- 2) Data manipulation: we integrated data from multiple sources to prepare our analysis

Summary

- 3) Data visualization: we made plots to explore patterns in our data
- 4) Data modeling: we made a model to capture the grouping patterns in data automatically, using visualization to explore the results of this modeling
- 5) Publishing: we abstracted our analysis into an application that allows us and others to perform this analysis over more datasets and explore the result of modeling using a variety of parameters