Movie projections using Relational Databases and Classification

The Wonderbolts
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Higher. Faster. Further.

Motivation

Using existing data, can we accurately predict how well upcoming movies will do?

(And will this make us lots of \$\$\$?)

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matter...

Find a pattern in these metrics, and use it to make a prediction

CHALLENGE ACCEPTED!!!

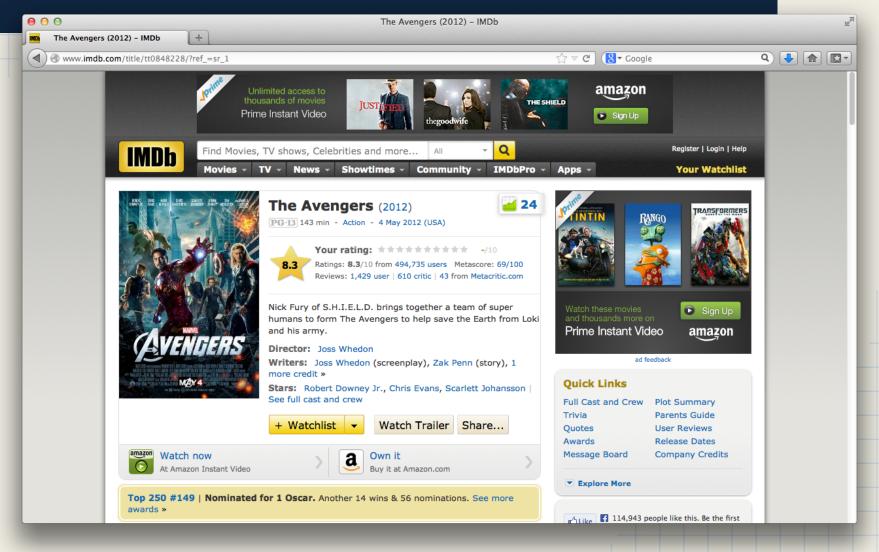


Where do <u>you</u> go when you need information on movies?



Follow up question: When you use Google, what is the first link that appears?

Internet Movie Database



IMDB API

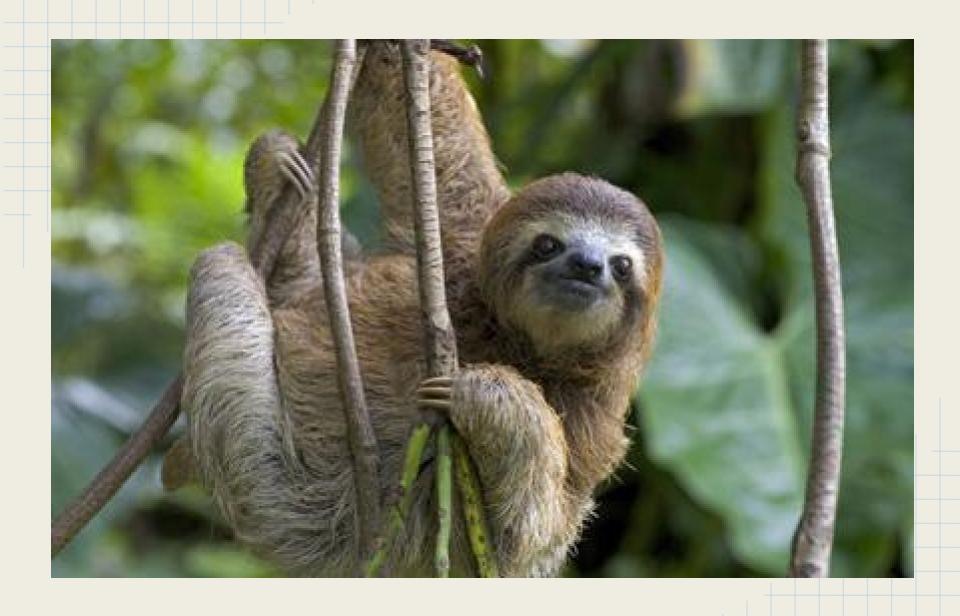
A lightweight, RESTful web interface to IMDb www.imdbapi.com

(Make JSON queries to fill our database)

IMDB API

A lightweight, RESTful web interface to IMDb www.imdbapi.com

-Lots of overhead in automating queries
-Huge data. Bandwidth isn't cheap (or plentiful)
-3,000 queries per hour limit
4,115,950 rows in 'person' table -> 57 days of processing
for ONE table



IMDB API would have been slow. Very, very slow.

IMDbPY

Open source project to retrieve and manage IMDb data imdbpy.sourceforge.net

- -Written in pure Python (with a few lines of C!)
 -Released under GPL 2 License
- -Can both retrieve data from IMDb directly (web)
 - -Can also parse data in IMDb's plain text files

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Minor forgotten detail...

IMDb releases subsets of the plain text file dumps of their database! www.imdb.com/interfaces/

49 files **6.75GB** when uncompressed

Part 3/3 - The Database

-IMDbPY doesn't support Oracle

(open source, yo)

Suggestion: SQLite -> Oracle

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Suggestion: SQLite -> Oracle

-SQLite doesn't work well with large data

-In addition, 4GB limit on Oracle tablesize == bad

MySQL to the rescue

Finally, loading the data

IMDb text files + IMDbPY + MySQL

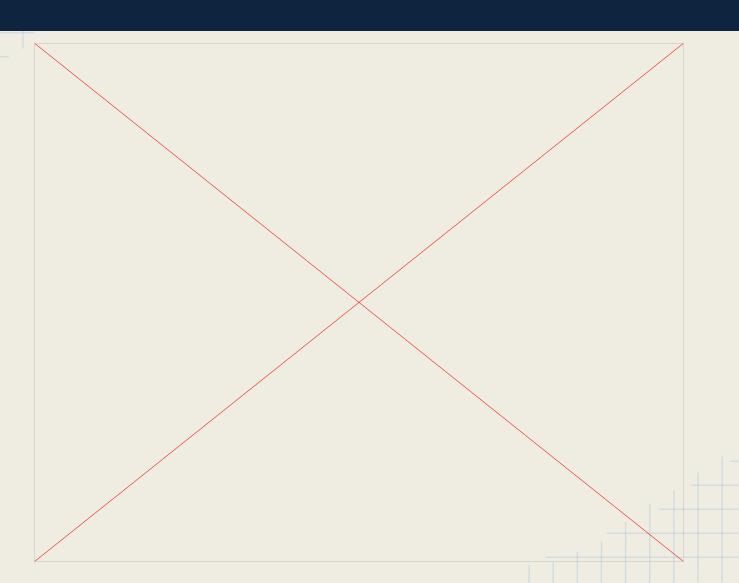
~1.5 hours to process in final run

Many attempts required to get it right:

- -Database issues
- -Dependency issues within Python
- -Resource issues (VPS vs. decent machine)

Lesson learned: Big data requires thoughtful planning and knowledge to set up and maintain effectively.

What does the data look like?



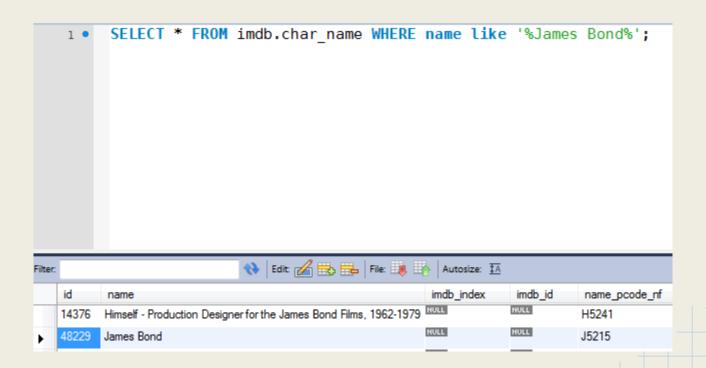
Let's see an example!

What if we wanted to actually do something with this data as is? Suppose we wanted to find out which actor played the best James Bond.



First things first...

Firstly we need to find the role_id of James Bond from the char_name table. Easy enough.



Now what?

Well now we need to find the person_id for every person who has played James Bond. We do this by looking in the cast_info table for the role_id.

```
Select * FROM imdb.cast_info where (person role id = 48229 and (role id = 1 or role id = 2));
                             ൜ | Edit: 🔏 📆 📇 | File: 🌉 📸 | Autosize: 🏗
        person_id
                     movie_id
                                 person_role_id
                                                  note
                                                           nr_order
                                                                      role_id
                                                 NULL
170773
        26494
                     1663805
                                 48229
                                                          14
                                                          NULL
                                                 NULL
185006
        29068
                     1969431
                                 48229
                                                                      1
684727
        96475
                     2266884
                                 48229
                                                 (as Ali G) 1
                                                                      1
                                                          NULL
773902
        108370
                     1886466
                                 48229
                                                 (voice)
                     1834552
                                 48229
                                                          59
831230
       116515
                                                                      1
        124908
                     2385540
                                 48229
                                                 (voice)
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        138066
                     1600995
                                 48229
                                                          1
1048662 146780
                                 48229
                     1600993
                                                 (voice)
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1048663 146780
                     1600995
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                    2399077
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1048675 146780
                                 48229
                                                 (voice)
                                                          NULL
                                                 NULL
1058788 147915
                    50674
                                 48229
                                                                      1
```

...Many queries later...

- Once we have the person_id list for people that played James Bond, we need to get scores for each movie where that actor played James Bond and find their average review score.
- We also need to limit our search to theatrical releases only.
- This involves a query that joins role_id, cast_info, title, movie_info_idx, and info_type tables...
- After taking half an hour to run the query we get the following data:

Actor	Average James Bond Film Score
Sean Connery	7.0
George Lazenby	6.8
Roger Moore	6.6
Timothy Dalton	6.6
Pierce Brosnan	6.5
Daniel Craig	7.5

What if we wanted to do something simpler?

What if we just wanted to decide how good an actor is by examining the average scores of his movies?

The query for this question looks like:

Select AVG(info) FROM (Select imdb.cast_info.movie_id, info, info_type_id, person_id, role_id FROM imdb.cast_info inner join imdb.movie_info_idx on imdb.cast_info.movie_id = imdb. movie_info_idx.movie_id) As T where (person_id = 1468525 and (role_id = 1 or role_id = 2) and info_type_id = 101);

Running this query takes upwards of 10 minutes and tells us that the late

Rod Steiger has an average review score of 6.2.



That seems like a lot of time and work...

If we want to look at hundreds of thousands of movies, and millions of actors we need to change something...



We need to change the world... or at least the structure of our database.

Data Manipulation

- 2.7 million columns
- 100K rows

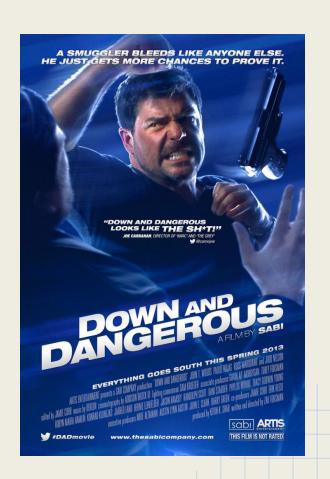
How do we deal with this much data?



What we lost...

- Actors not in a movie
- Redundant entries
- Independent films
- Low-budget films
 - < \$1,000,000</p>



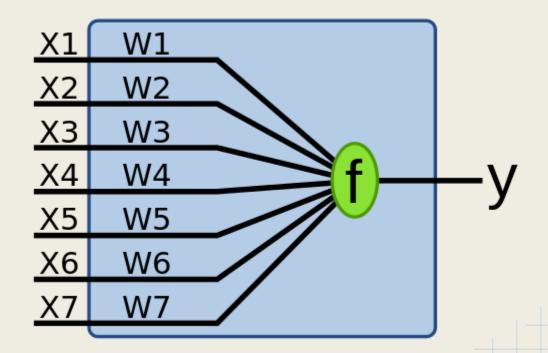


dataGet.py

- Matlab hates us
- Store data in text files
 - o data 2000.txt
 - target_2000.txt
 - Read in data

Perceptron

- Many inputs
- Many weights



How it works...

- Dot products
 - Feature vector
 - Weight vector

$$f(x) = \begin{cases} 1 & \text{if } w \cdot x + b > 0 \\ 0 & \text{otherwise} \end{cases}$$

- Minimize test error
 - misclassified / total

Naive Bayes Classifier

- Probabilities
 - P(Class|Features)
- Learns P(F|C)

$$p(C|F_1,\ldots,F_n) = \frac{1}{Z}p(C)\prod_{i=1}^n p(F_i|C)$$

Computes P(C|F) to predict

6.5 Star Threshold

```
Brians-MacBook-Pro-2:Desktop salterbw$ python doTests.py
2011
2012
Testing error: 0.349799732977
Naive Bayes Error: 0.427236315087
Brians-MacBook-Pro-2:Desktop salterbw$ ■
```

7 Star Threshold

```
Brians-MacBook-Pro-2:Desktop salterbw$ python doTests.py
2011
2012
Testing error: 0.217623497997
Naive Bayes Good Error: 0.229639519359
Naive Bayes Bad Error: 0.229639519359
Brians-MacBook-Pro-2:Desktop salterbw$ ■
```

What comes next...

- Increase Timespan
- 2. More Features
- 3. Multiclass
- 4. Multi-layers

Summary

1. Big data == Lots of time to load

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- 2. Big data == Lots of time to maintain

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- 1. Big data == Lots of time to load
- 2. Big data == Lots of time to maintain
- 3. Big data == Lots of time to analyze
- 4. Make good, smart choices about how/what you are doing
- 5. Challenge defeated, @ArtsJournal

FIN

