

A large, abstract network graph is positioned in the upper right corner of the slide. It consists of numerous small, semi-transparent gray dots connected by thin, light gray lines, forming a complex web-like structure.

FAME OR FLOP: *PREDICTING THE SUCCESS OF A FILM USING NATURAL LANGUAGE PROCESSING & MACHINE LEARNING*

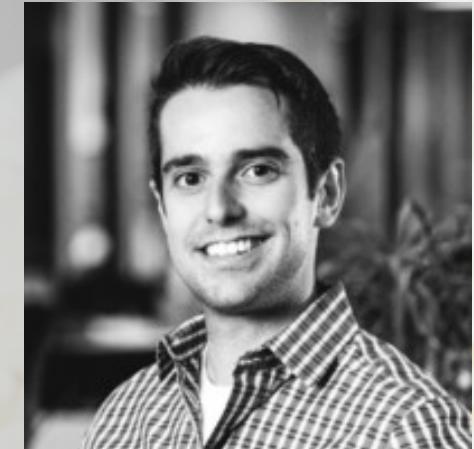
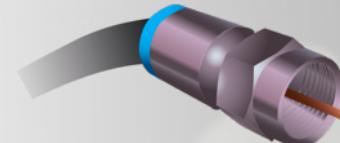
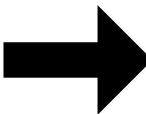
AUG 14 2019

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ABOUT ME

MAX BAMBERGER



Summary

I'm a Management Consultant with 7+ years of experience as a professional consultant in the Cable, Telecom and Media/Advertising industries.

Interesting Facts about me (only one is a lie)

- I flew over 350,000 miles in the last 4 years.
- I ran into a grizzly bear on a hike in Canada
- My impressions are scary good
- I love to cook
- I can recite the pledge of allegiance in Spanish
- I once slept in Shintoist monestary for a week in Japan
- I accidentally spelled my name wrong on my diploma
- And lastly..... I love movies!

Technical Skills

Languages / Platforms:

Python (libraries: Numpy, Pandas, Sci-kit Learn, Scipy, StatsModels, Matplotlib, NetworkX, Seaborn, SpaCy, NLTK, boto3, Flask), PySpark

SQL, MongoDB, AWS, Docker, VBA, R Studio, Tableau,

Machine Learning / Statistics:

Probability & Statistical Analysis, Hypothesis Testing (Bayesian as well as Frequentist approaches),

Experienced in building:

Supervised Learning models:

- Gradient Boosting Trees
- Random Forrest
- Linear/Logistic Regression
- Naïve-Bayes Classification

Unsupervised Learning models:

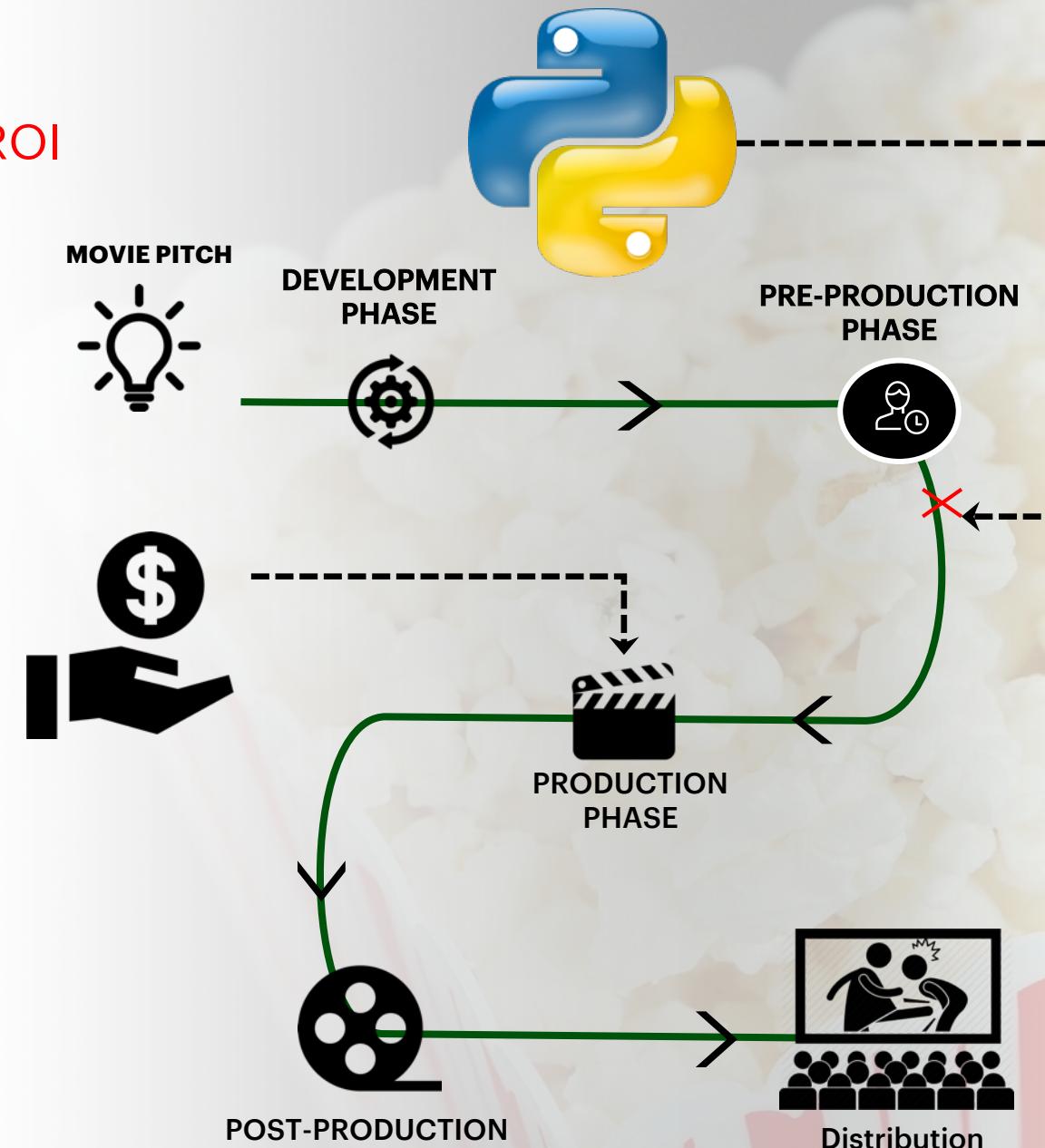
- Recommendation Systems
- Clustering (K-means)
- Dimensionality Reduction (PCA, NMF, SVD)

PROJECT MOTIVATION

EARLY PREDICTION OF MOVIE SUCCESS AND ROI

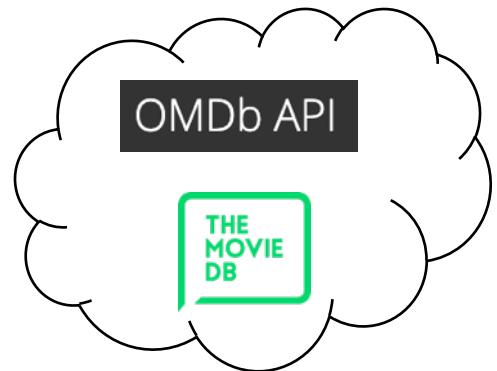
Current Challenge:

- **In Hollywood, the stakes are high:**
Sustained success can mean fame and fortune, but 70% of movies flop!
- **What if you could know with more certainty if a movie has a real shot at success before your money is sunk?**
- **Hollywood already does this.** Movies tend to follow a formula. What is that formula? That's what I set out to find!



THE DATA PIPELINE & MACHINE LEARNING

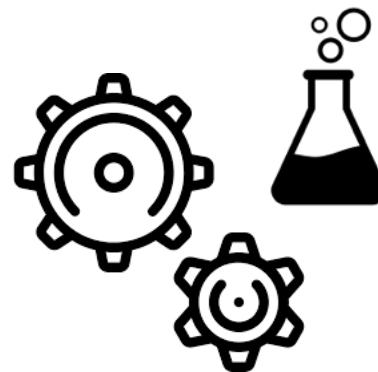
EARLY PREDICTION OF MOVIE SUCCESS AND ROI



Gather and clean data

Data is ingested through two APIs:

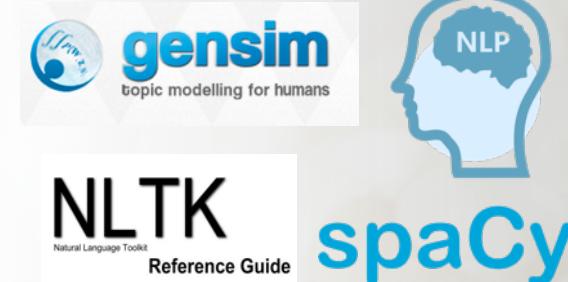
- [Open Movie Database \(OMDB\) API](#) directors, actors, writers and awards
- [The Movie Database \(TMBD\) API](#) budget and revenue information
- Define Success:
$$\text{Profit} = \text{Revenue} - (3 \times \text{Budget})^*$$
- Other ways to define?



Feature Engineer

Features are derived and added to the data. Some examples:

- Director/Writer/Actor popularity
- Last movie' Oscar Performance
- Studio Performance
- Historical Chemistry
- Release proximity to other films



Train The Topic Model

Plot Synopsis text: fed to a Latent Dirichlet Allocation Algorithm. Producing:

- 20 general topics
- Percentage contribution scores to each topic



Train The Classifier Model

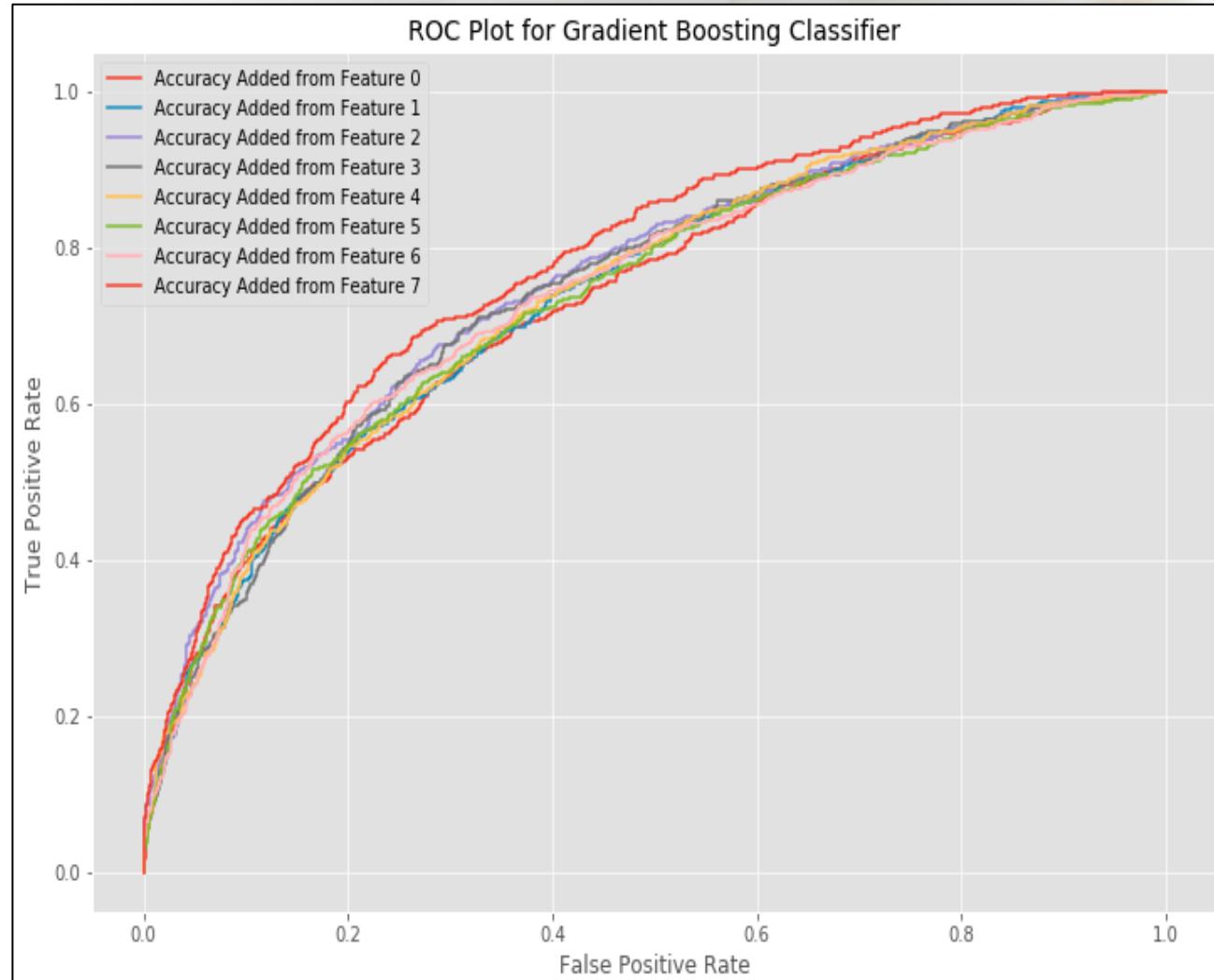
Supervised learning model is trained using ~250 features:

- GradientBoosting Classifier
- XGBoost & Random Forest yield similar results

FEATURE ENGINEERING

A DRILL DOWN OF EACH FEATURE

1. `add_star_power()` #=> Actor popularity
2. `add_writer_power()` #=> Writer popularity
3. `add_director_power()` #=> Director popularity
4. `last_movie_award()` #=> Oscars from Actors/Directors/Writers' last movie
5. `top_production_score()` #=> Best prod studios
6. `add_chem_factor(verbose)` #=> count of past collaborations between crew-member pairs
7. `add_macro_trend()` #=> avg revenue in last year
8. `add_release_proximity()` #=> how close to o



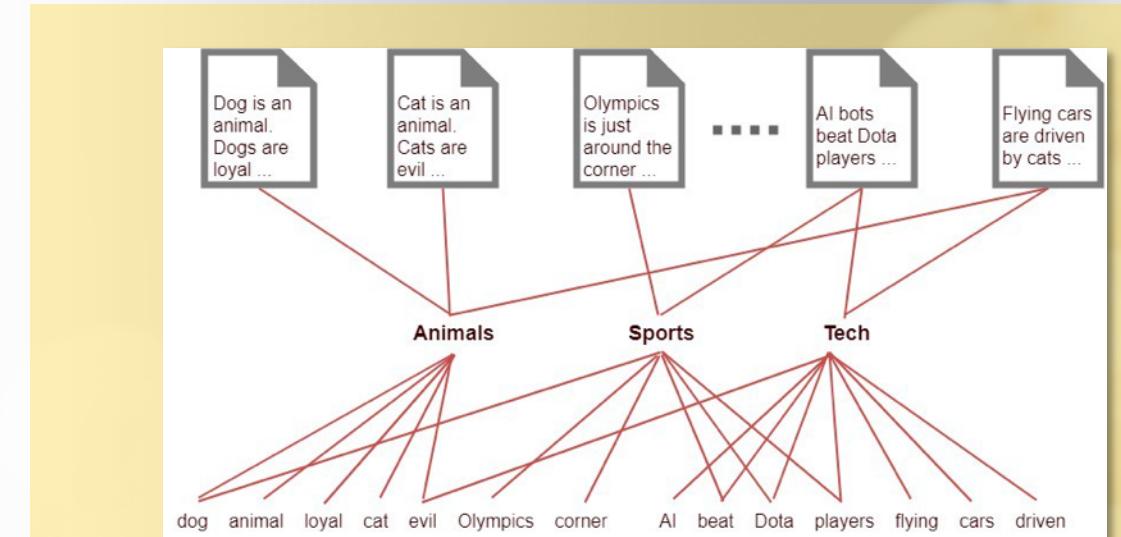
TOPIC MODELING

LATENT DIRICHLET ALLOCATION (LDA)

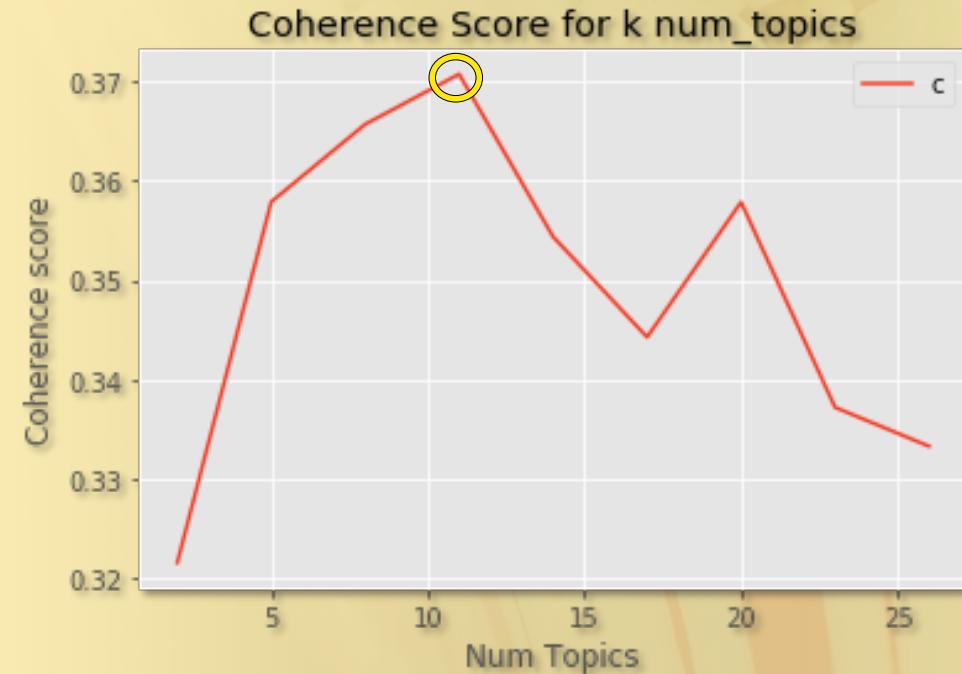
What is LDA / Topic Modelling?



- Topic modelling refers to the task of identifying topics that best describes a set of documents.
 - LDA represents documents as **mixtures of topics** represented as words with certain probabilities
 - Assumes documents (plots) are generated probabilistically from these topics
 - Algorithm requires a parameter k for # of latent topics I had to set
 - Coherence score
 - Perplexity score
 - Optimal=11



$$\gamma^*, \phi^*, \lambda^* = \operatorname{argmin}_{(\gamma, \phi, \lambda)} D(q(\theta, \mathbf{z}, \beta | \gamma, \phi, \lambda) || p(\theta, \mathbf{z}, \beta | \mathcal{D}; \alpha, \eta))$$



TOPIC MODELING (CON'T)

LATENT DIRICHLET ALLOCATION (LDA)

Topic Model Output:

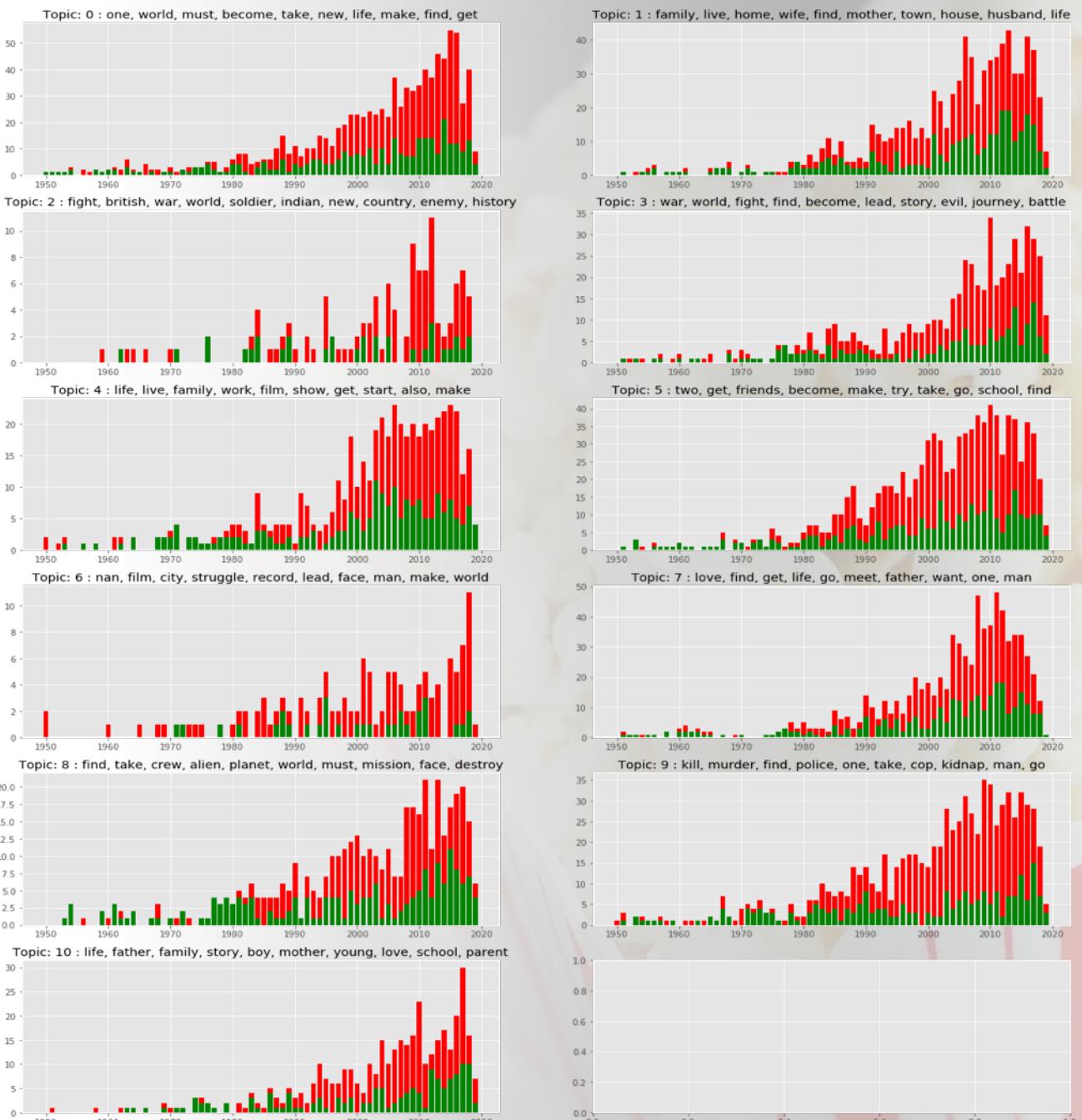
```
[ (0, '0.008*"one" + 0.008*"world" + 0.007*"must" + 0.006*"become" + 0.006*"take" ' '+'+ 0.006*"new"' ),  
(1, '0.023*"family" + 0.012*"live" + 0.010*"home" + 0.010*"wife" + 0.009*"find" ' '+'+ 0.009*"mother"' ),  
(2, '0.008*"fight" + 0.008*"british" + 0.008*"war" + 0.007*"world" + ' '0.006*"soldier" + 0.006*"indian"' ),  
(3, '0.009*"war" + 0.008*"world" + 0.008*"fight" + 0.007*"find" + 0.007*"become" ' '+'+ 0.007*"lead"' ),  
(4, '0.014*"life" + 0.012*"live" + 0.009*"family" + 0.006*"work" + 0.006*"film" ' '+'+ 0.006*"show"' ),  
(5, '0.011*"two" + 0.010*"get" + 0.007*"friends" + 0.006*"become" + 0.006*"make" ' '+'+ 0.006*"try"' ),  
(6, '0.018*"nan" + 0.016*"film" + 0.006*"city" + 0.006*"struggle" + ' '0.005*"record" + 0.005*"lead"' ),  
(7, '0.015*"love" + 0.013*"find" + 0.012*"get" + 0.012*"life" + 0.011*"go" + ' '0.009*"meet"' ),  
(8, '0.011*"find" + 0.008*"take" + 0.008*"crew" + 0.007*"alien" + 0.007*"planet" ' '+'+ 0.007*"world"' ),  
(9, '0.018*"kill" + 0.012*"murder" + 0.012*"find" + 0.008*"police" + 0.007*"one" ' '+'+ 0.007*"take"' ),  
(10, '0.024*"life" + 0.010*"father" + 0.010*"family" + 0.010*"story" + ' '0.009*"boy" + 0.007*"mother"' )]
```

TOPIC MODELING (CON'T)

LATENT DIRICHLET ALLOCATION (LDA)

How does this help the classification?

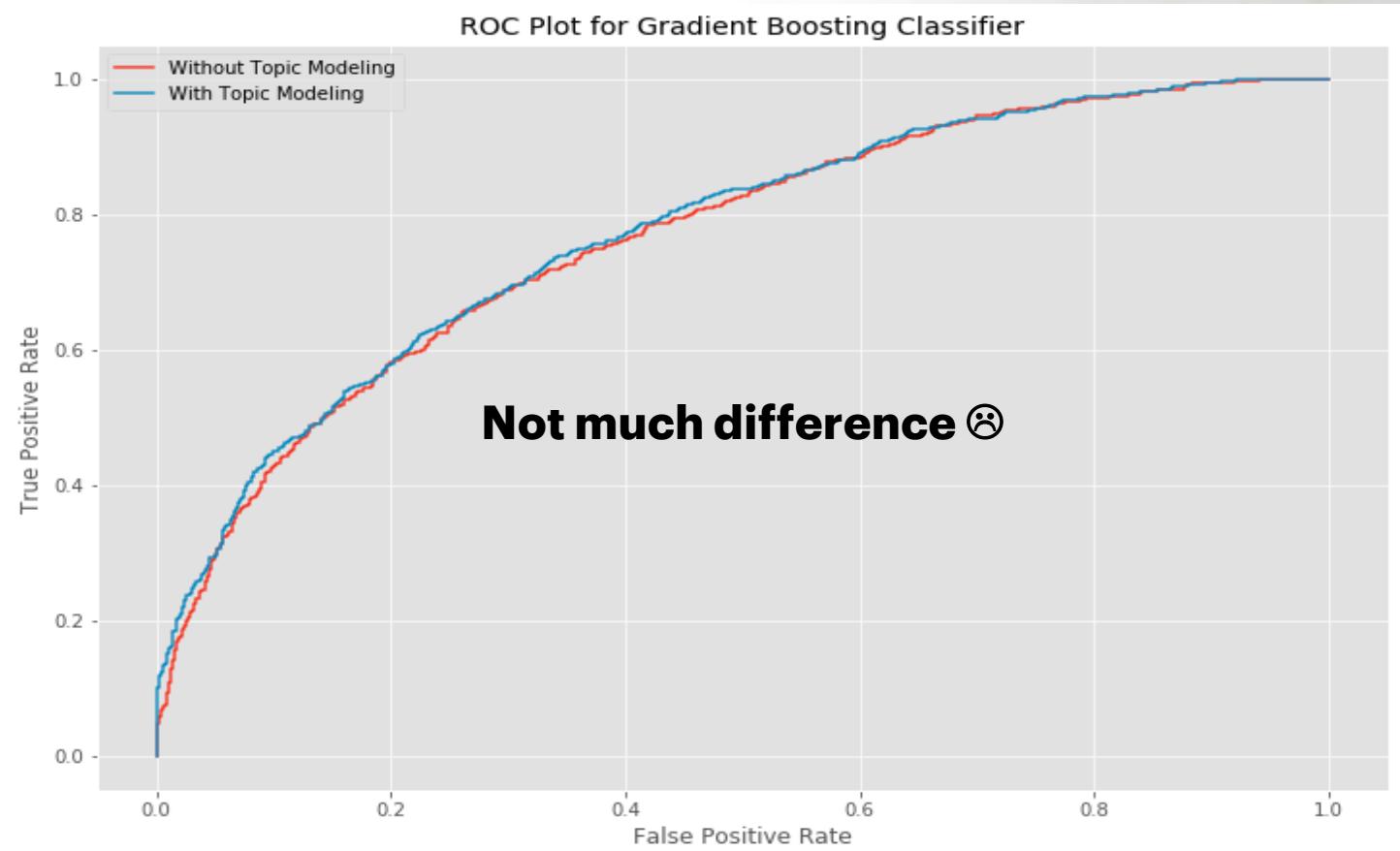
- Each movie contributes to a topic by some percentage
- **In theory** some topics are more profitable than others
- **Conclusion:**
 - Its interesting but doesn't help much
 - Need to segment the data better (i.e. last 5 years)
- **Challenges:** environmental issues using LDA Mallet



TOPIC MODELING (CON'T)

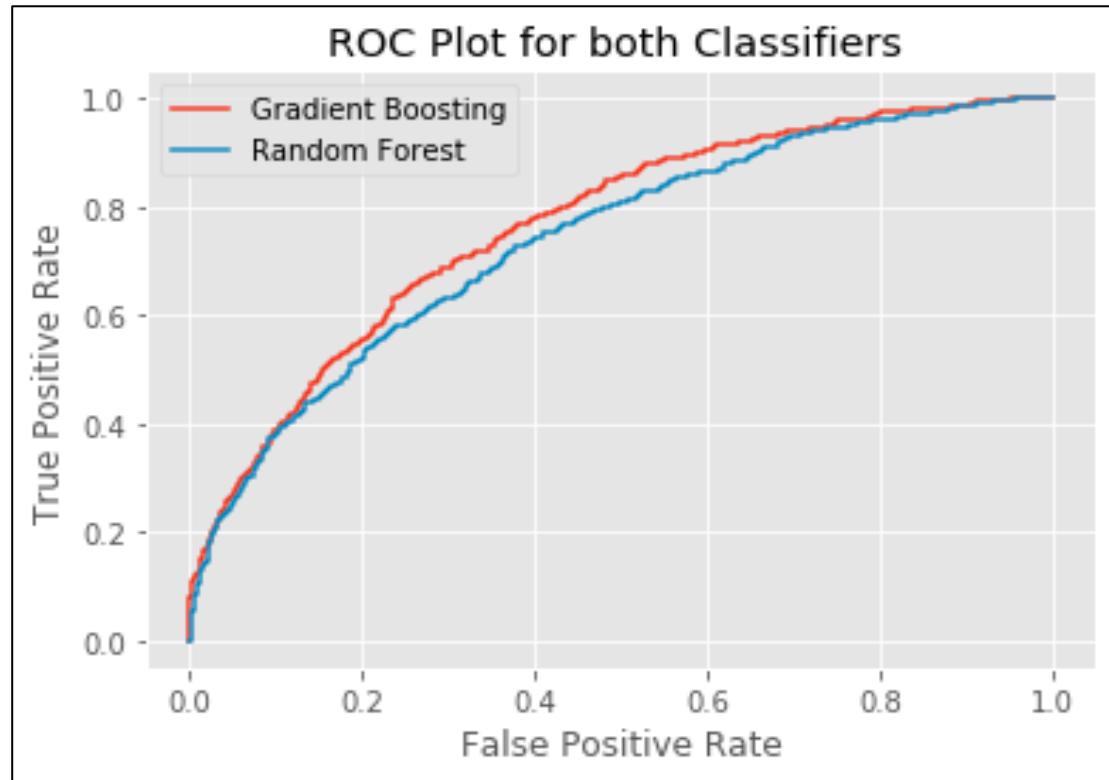
LATENT DIRICHLET ALLOCATION (LDA)

How does this help the classification?



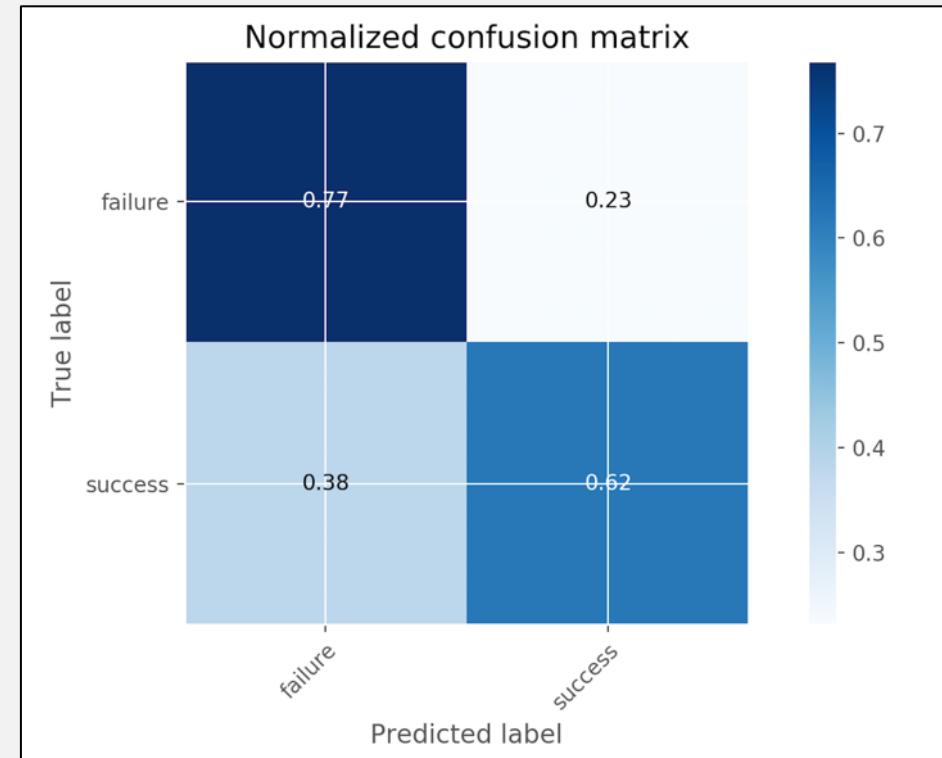
EVALUATION

EARLY PREDICTION OF MOVIE SUCCESS AND ROI



- **Use Gradient Boosting!:**
 - Exhaustive GridSearchCV
 - Sample_weights / Class_weights
- **Challenges:** Time series data leakage
- **Conclusion:** Need a high threshold – model is better at finding the successes than avoiding false negatives

Accuracy : 0.7231
ROC AUC : 0.7761
Recall : 0.6675
Precision: 0.6132



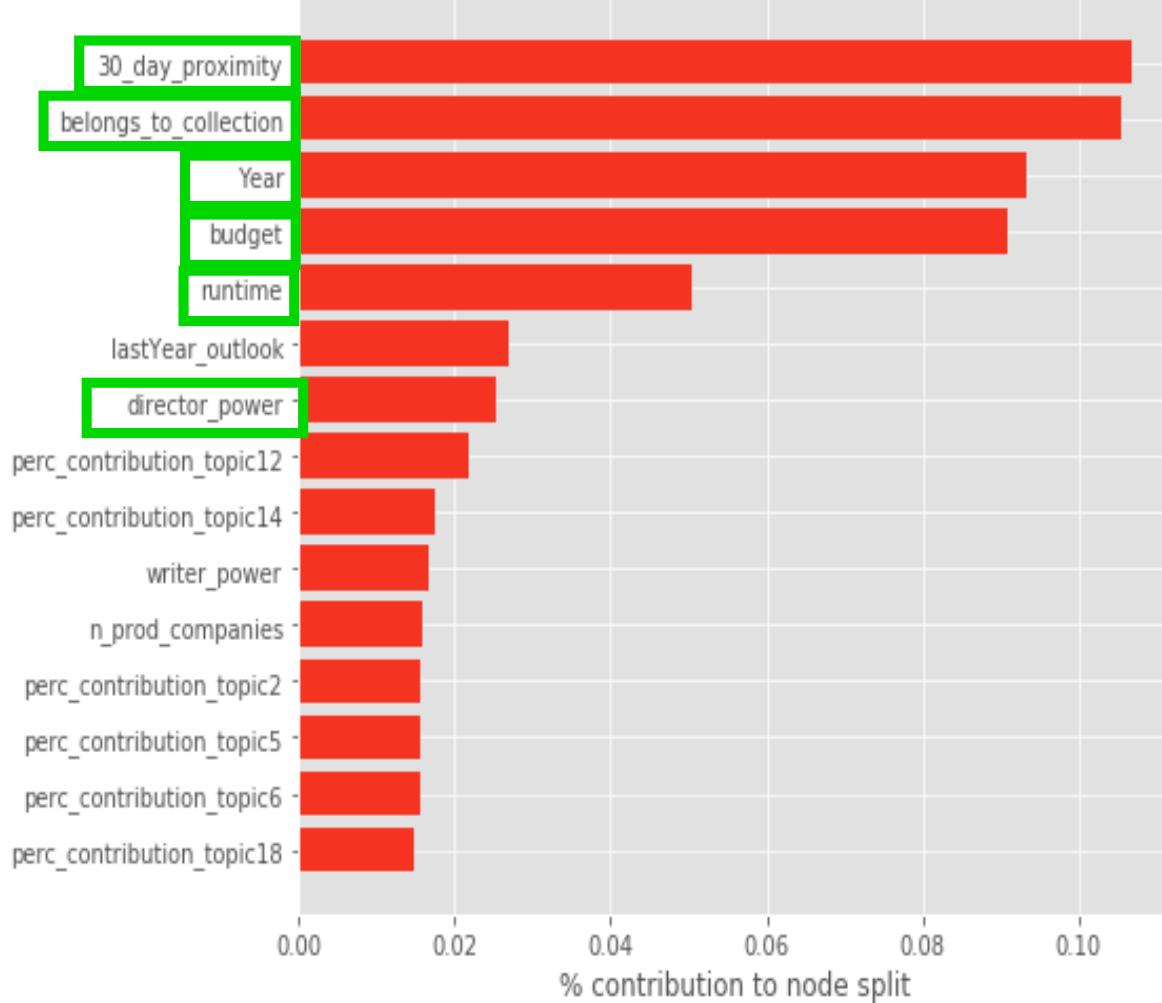
EVALUATION

EARLY PREDICTION OF MOVIE SUCCESS AND ROI

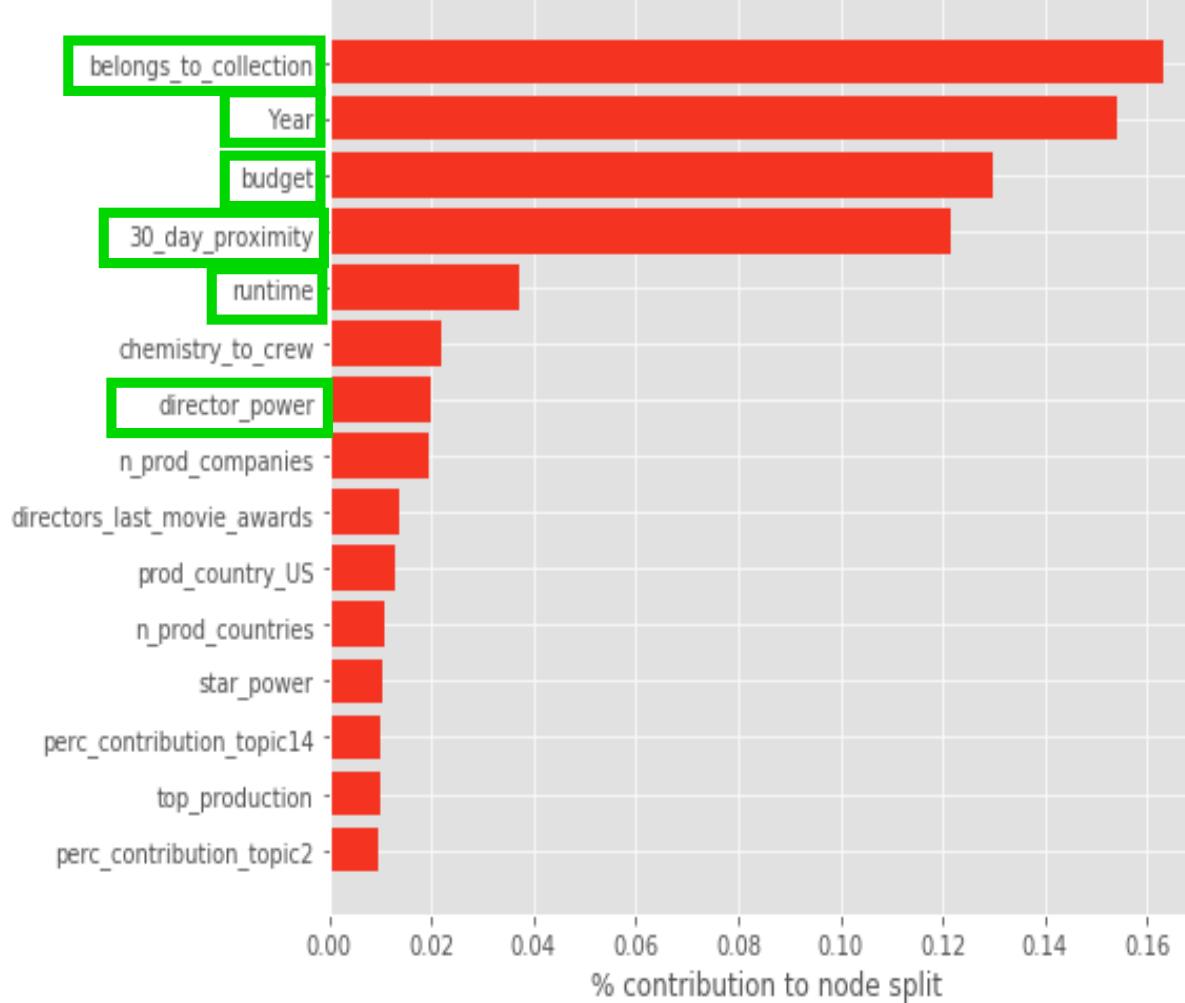
Demo: Lets make a [successful] movie!!

Feature Importance – ‘The Formula’ to a successful movie!

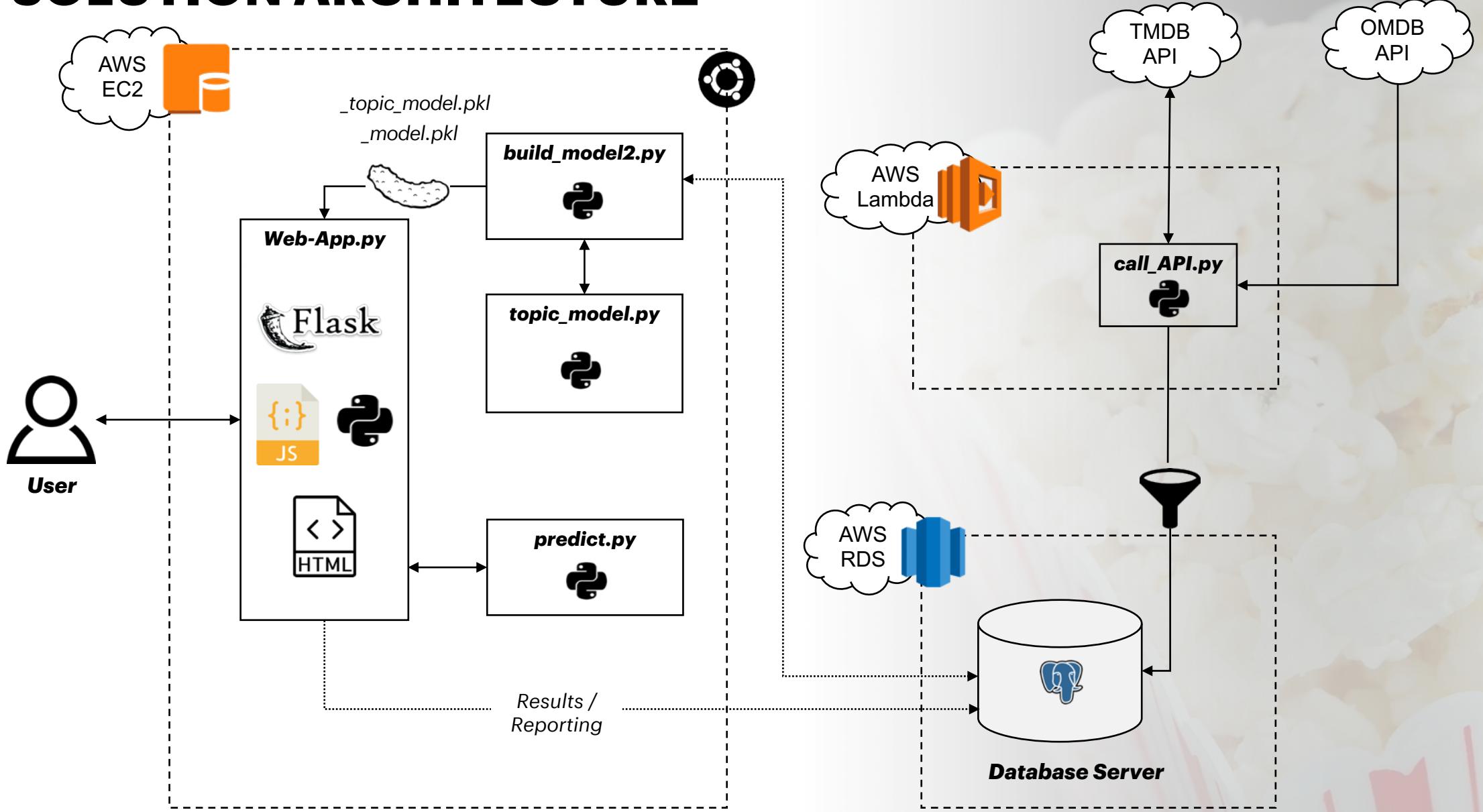
Top 15 Features from Random Forest Model



Top 15 Features from Gradient Boosting Model



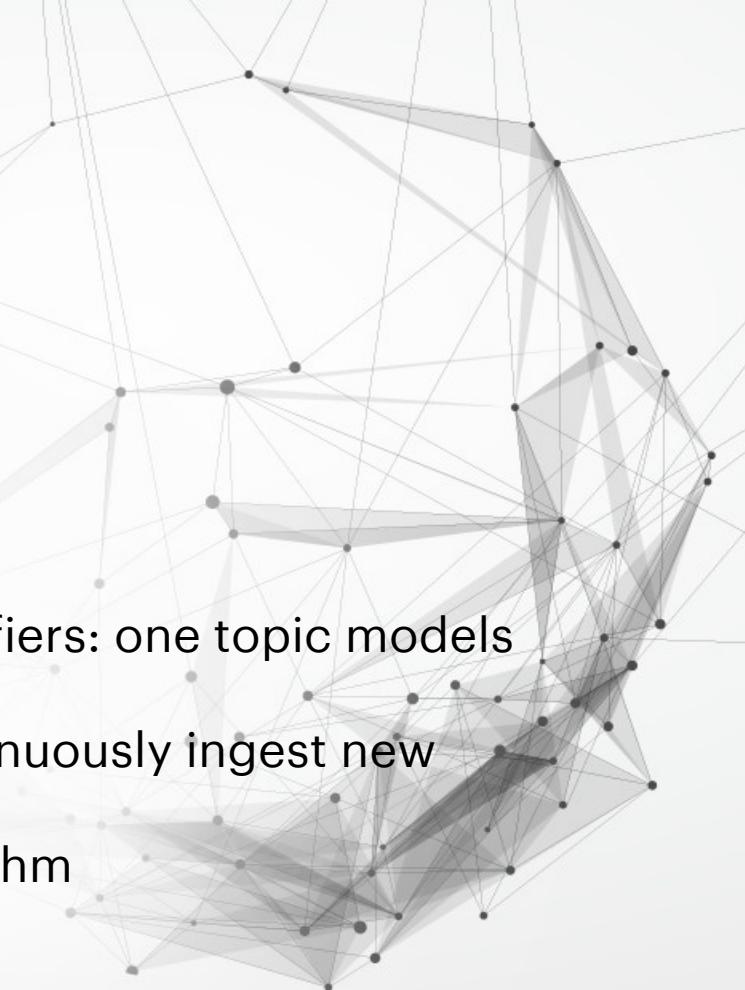
SOLUTION ARCHITECTURE



NEXT STEPS

PHASE 2.0:

1. Clean the data better (e.g. remove wrestling matches)
2. Optimize model with a more exhaustive grid search (XGBoost)
3. Add more features:
 - Measuring success within genre
 - NLP / Topic model entire movie scripts
4. Improve the Topic modeling with more meticulous NLP
5. Fork the data pipeline into two sets of data and separate classifiers: one topic models just the movies in the last 5 years
6. Build the rest of the architecture and database servers to continuously ingest new movie data and update model monthly
7. More analysis on the textual data I'm feeding to the LDA algorithm
8. Improve the Web App:
 - Make case-insensitive
 - Set range parameters (e.g. on Budget, Avg Revenue etc.)
 - Make prettier results page
 - Make form more intuitive (i.e. Genre checklist, specify which fields are optional)





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<https://www.quora.com/What-is-the-average-return-on-investment-for-a-Hollywood-movie>

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