Using scores to improve language modelling of movie plot summaries

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Presentation outline

1. Problem formulation
2. Models
3. Approach
4. Dataset
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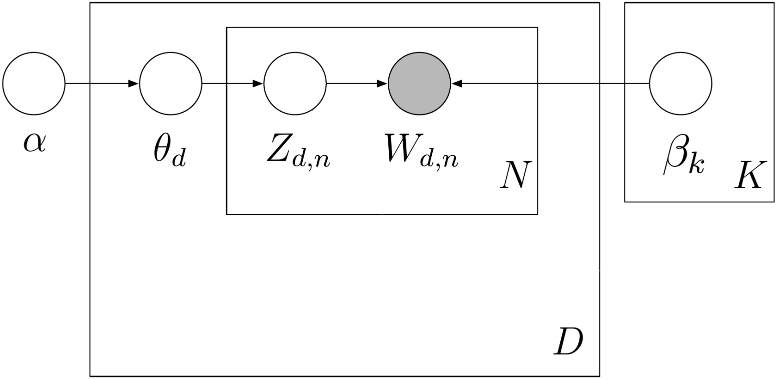
Problem formulation

- Is there any correlation between the score of a movie and the contents of its script?
- Can we use the score to better model a movie corpus?

Models

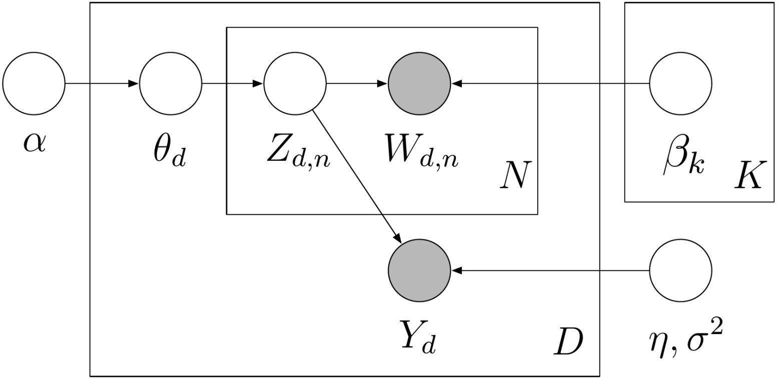
Latent Dirichlet Allocation:[1]



[1] Image taken from the paper "Supervised topic models" by David M. Blei and Jon D. McAuliffe (2007)

Models

Supervised Latent Dirichlet Allocation:[2]



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Approach

Our collapsed Gibbs sampler:

$$p(z_{di} = k \mid Z^{\setminus i}, S, W, \alpha, \beta, \eta, \sigma) \propto \left[\prod_{k'} \frac{\prod_w \Gamma(N_{k'w}^{\setminus i} + \mathbb{I}(k' = k \wedge w = w_{di}) + \beta)}{\Gamma(N_{k'}^{\setminus i} + \mathbb{I}(k' = k) + W\beta)} \right] \times \underbrace{\mathcal{N}\left(s_d \,\middle|\, \eta^T \cdot \frac{N_{dk'}^{\setminus i} + \mathbb{I}(k' = k)}{N_d}, \sigma \right)}_{\text{Movie score term}} \prod_{k'} \Gamma(N_{dk'}^{\setminus i} + \mathbb{I}(k' = k) + \alpha)$$

Better implemented in log-space probabilities to avoid numerical problems.

Approach

Estimating the global score hyperparameter η:

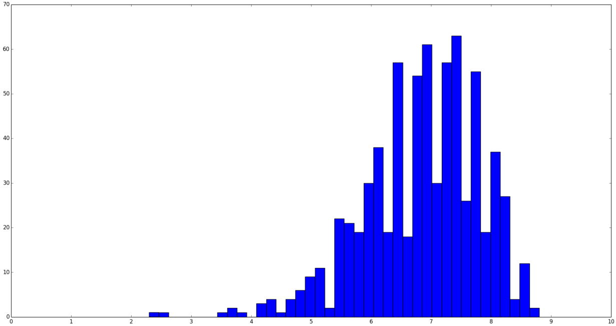
$$\eta_k^{new} \leftarrow (1-\gamma)\eta_k^{old} + \gamma \frac{\sum_d \frac{N_{dk}}{N_d}\left(s_d - \sum_{k'\neq k} \eta_{k'}^{old} \frac{N_{dk'}}{N_d}\right)}{\sum_d \left(\frac{N_{dk}}{N_d}\right)^2 + \varepsilon}$$

Where:

- $1 \gg \gamma > 0$ in order for the previous series to converge.
- $1 \gg \varepsilon > 0$ is a smoothing constant.

Dataset

- We made scripts to crawl `http://www.imsdb.com/` for movie scripts and then search `http://www.imdb.com/` for movie scores and plot summaries.
- We got a database with ≈ 700 movies.
- Movie score distribution (from 0 to 10):

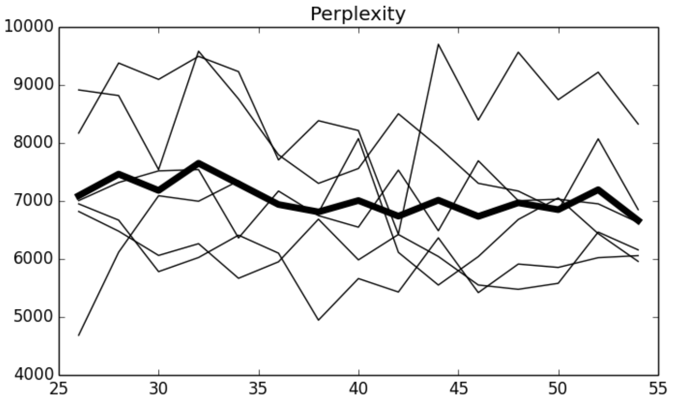


Dataset

- Tokenization → stemming → pruning
- We prune words appearing only on a single movie (avoids overfitting) or within a stop list.
- Total number of tokens $\approx 12.7 \cdot 10^6$
- Number of unique tokens ≈ 35000
- Average number of tokens within a movie summary ≈ 75
- Average number of tokens within a movie script ≈ 18000

Results

- Initial selection of 30 movies (20 training / 10 testing) with balanced scores.
- Using 10 topics and no scores.



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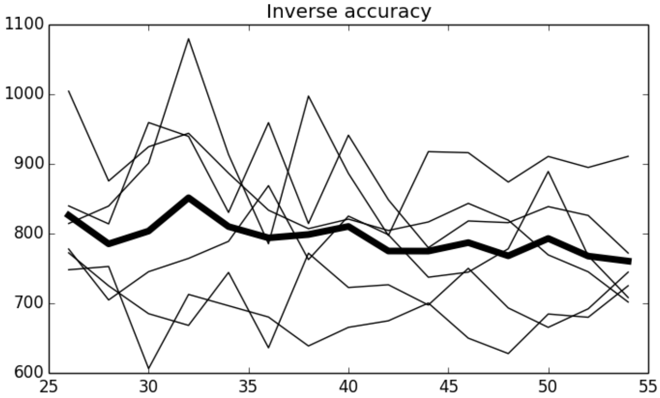

Discussion

Challenges

- Improve speed of the collapsed Gibbs sampler.
- Use the movie scripts instead of the movie summaries.
- Use both the movie scripts and summaries.
- Incorporate more information into the model, such as the movie genre.