Using scores to improve language modelling of movie plot summaries

J. Sáez Gómez, R. vd Heijden, F. Stablum

Problem formulation

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Presentation outline

Problem formulation

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- 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]

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

Models

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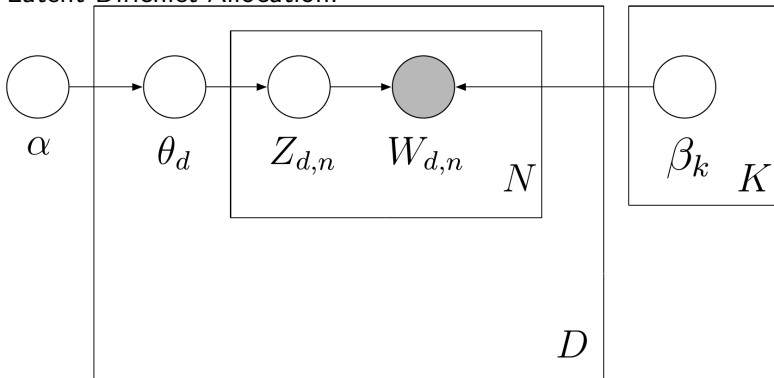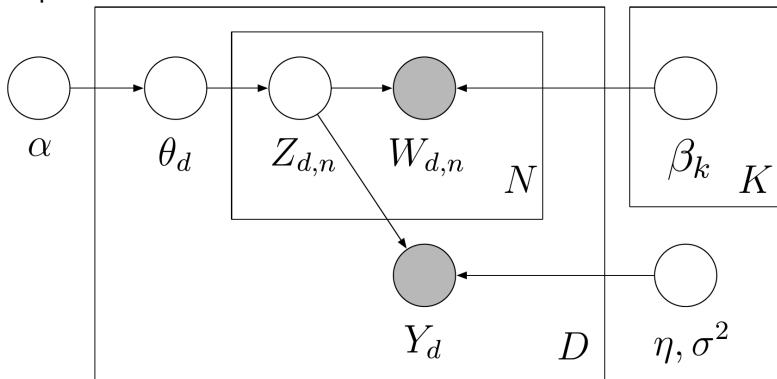Problem
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Supervised Latent Dirichlet Allocation:[2]

Approach

Our collapsed Gibbs sampler:

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

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

Approach

Estimating the global score hyperparameter η:

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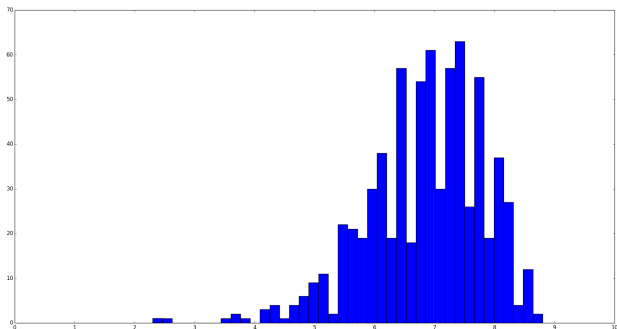
Where:

- $1 \gg \gamma > 0$ 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 $\rightarrow$ stemming $\rightarrow$ 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.

Perplexity

Results

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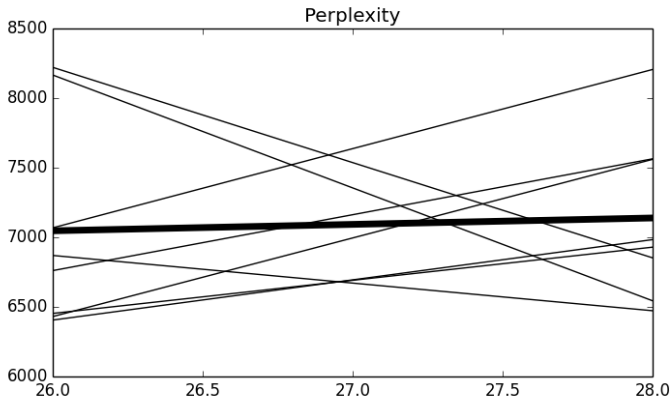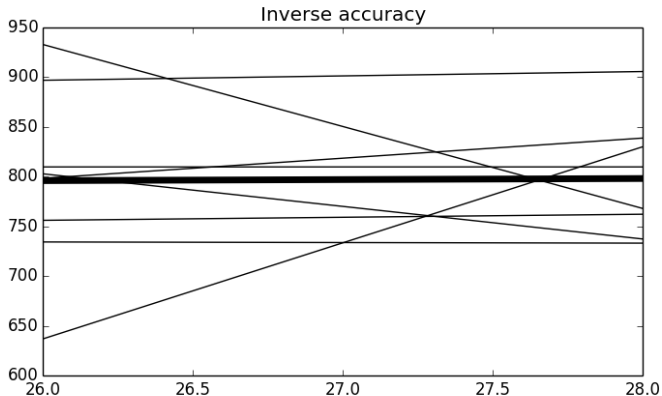
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Challenges

- 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.