

# DIFFERENTIAL COUNT ANALYSIS WITH A TOPIC MODEL

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**1. Motivation, and overview of methods.** The aim of this document is to derive, from first principles, a method for analysis of differential gene expression using a topic model (also known as “grade of membership model” [4]). This method may have other uses — say, to identify “key words” in a topic modeling analysis of text documents — but since our main motivation is analysis of gene expression data, we describe the methods with that application in mind.

For motivation, we begin with the “log-fold change” statistic commonly used in microarray and RNA sequencing experiments to quantify expression differences between two conditions (e.g., [3, 5]). The log-fold change for gene  $j$  and condition  $k$  is a ratio of two conditional expectations,

$$(1) \quad \text{lfc}(j, k) \equiv \log_2 \frac{E[x_j \mid \text{condition} = k]}{E[x_j \mid \text{condition} \neq k]},$$

where  $x_j$  is the measured expression level (e.g., UMI count) of gene  $j$ .<sup>1</sup>

The statistic (1) is a measure of *absolute* change in expression level between two conditions. It is often preferable to measure *relative* change, say, change in gene expression relative to the total expression in each sample [2]. As we will see, a topic modeling perspective provides a natural way to analyze either absolute or relative change in gene expression.

Topic modeling brings two new twists to analysis of differential gene expression:

1. In conventional differential expression analysis, each sample is assigned to a single condition; in topic modeling, the assignments to each topic are *proportional*.
2. In conventional differential expression analysis, all expression measurements in a sample are assumed to be from the same condition; in topic modeling, it is the genes that are assigned to the topics, not the samples.

These two points need to be accounted for in developing the new methods for differential expression analysis.

**1.1. The binomial model.** We begin with a simple binomial model that predicts expression of a single gene given the proportional assignments to a topic:

$$(2) \quad x_i \sim \text{Binom}(s_i, \pi_i).$$

Here,  $x_i$  is the expression level of the target gene in sample  $i$ ,  $s_i$  is the total expression in sample  $i$ , and  $\text{Binom}(n, \theta)$  denotes the binomial distribution with  $n$  trials and success probability  $\theta$ . In this simple model, the binomial probabilities are defined as

$$(3) \quad \pi_i = (1 - q_i)p_0 + q_i p_1,$$

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<sup>1</sup>Defining  $x_{jk}$  as the total gene expression for gene  $j$  among all samples (expression profiles) in condition  $k$ ,  $x_j$  as the total gene expression for gene  $j$  in all samples,  $n_k$  as the number of samples in condition  $k$ , and  $n$  as the total sample size, the log-fold change can be computed as  $\text{lfc}(j, k) = \log_2 \left\{ \frac{x_{jk}}{x_j - x_{jk}} \times \frac{n - n_k}{n_k} \right\}$ .

where  $q_i \in [0, 1]$  is the (known) proportion of sample  $i$  that is attributed to the topic, and  $p_0, p_1 \in [0, 1]$  are two unknowns to be estimated.<sup>2</sup>

Statistical inference with this simple binomial model implements analysis of differential gene expression. In particular,  $\log_2(p_1/p_0)$  is the *relative log-fold change*. To show that this is so, consider the following statistical process for generating the counts  $x_1, \dots, x_n$ :

- for  $i = 1, \dots, n$ 
  1. for  $t = 1, \dots, s_i$ 
    - (a) Sample a topic,  $z_{it} \sim \text{Binom}(1, q_i)$ .
    - (b) Sample a gene,  $w_{it} | z_{it} \sim \begin{cases} \text{Binom}(1, p_1) & \text{if } z_{it} = 1 \\ \text{Binom}(1, p_0) & \text{otherwise.} \end{cases}$
  2.  $x_i \leftarrow w_{i1} + \dots + w_{is_i}$ .

In this statistical process,  $p_1 = p(w_{it} = 1 | z_{it} = 1)$  is the conditional probability that the gene is expressed given membership to the topic, and  $p_0 = p(w_{it} = 1 | z_{it} = 0)$  is the probability that the gene is expressed when not belonging to the topic. Therefore, we have

$$(4) \quad \log_2 \frac{p_1}{p_0} = \log_2 \frac{p(w_{it} = 1 | z_{it} = 1)}{p(w_{it} = 1 | z_{it} = 0)},$$

which is the relative log-fold change statistic given the proportional topic assignments  $q_1, \dots, q_n$ . The binomial model (2) can in fact be derived from this statistical process (proof not shown). Therefore, estimating  $p_0, p_1$  for the binomial model (2) provides an estimate of the relative log-fold change (4).

**1.2. The Poisson model.** A Poisson model similar to the binomial model (2) leads to a method for estimating *absolute* log-fold change. We proceed in a similar way. The Poisson model is

$$(5) \quad x_i \sim \text{Poisson}(\lambda_i),$$

where the Poisson rates are defined as

$$(6) \quad \lambda_i = (1 - q_0)f_0 + q_i f_1,$$

**2. The multinomial topic model and Poisson non-negative matrix factorization.** Here we briefly describe the multinomial topic model, and its connection to Poisson non-negative matrix factorization (Poisson NMF).

We begin with the “bag of words” description, which was used to describe the LDA model [1]. In this view, each document (or gene expression profile)  $i$  is represented as a vector of terms/genes,  $w_i = (w_{i1}, \dots, w_{is_i})$ , where  $s_i$  is the size of document  $i$ . (The order of the words or genes appearing in this vector doesn’t matter, hence the “bag of words.”) Each  $w_{it} \in \{1, \dots, m\}$  is term/gene  $j$  with probability  $p(w_{it} = j | z_{it} = k) = f_{jk}$ , in which we have introduced  $z_{it}$ , a variable indicating which topic  $k \in \{1, \dots, K\}$  the word/gene is drawn from. The topic indicator variables for document  $i$  are in turn generated according to  $p(z_{it} = k) = l_{ik}$ .

<sup>2</sup>This is a special case of a well-studied model in econometrics called the *linear probability model* [6]. The linear probability model would be typically written as  $\pi_i = \beta_0 + q_i \beta$ , where  $\beta_0 = p_0$  and  $\beta = p_1 - p_0 \in [-1, +1]$ . This is a regression model for the binomial probability  $\pi_i$ , in which  $\pi_i$  increases linearly with topic proportion  $q_i$ .

This process also defines a *multinomial* model for an  $n \times m$  matrix of counts  $x_{ij}$ :

$$(7) \quad x_{i1}, \dots, x_{im} \sim \text{Multinom}(x_{i1}, \dots, x_{im}; s_i, \pi_i),$$

where  $x_{ij} = \sum_{t=1}^{s_i} \delta_j(w_{it})$  is the number of times term/gene  $j$  appears in document/cell  $i$ , and the probabilities  $\pi_{ij}$  are weighted sums of the “factors”  $f_{jk}$ ,

$$(8) \quad \pi_{ij} = \sum_{k=1}^K l_{ik} f_{jk}.$$

The log-likelihood for the multinomial topic model, ignoring terms that do not depend on the model parameters, has a simple expression:

$$(9) \quad \log p(x) = \sum_{i=1}^n \sum_{j=1}^m x_{ij} \log(\sum_{k=1}^K l_{ik} f_{jk}).$$

As we have shown elsewhere, the multinomial topic model is closely related to a Poisson non-negative matrix factorization of the count data,

$$(10) \quad x_{ij} \sim \text{Poisson}(\lambda_{ij}),$$

where  $\lambda_{ij} = \sum_{k=1}^K \hat{l}_{ik} \hat{f}_{jk}$ . Given a Poisson NMF fit, an equivalent multinomial topic model can be easily recovered, as we have shown elsewhere.

**3. Gene expression differences in topics.** Returning to the question of assessing differential gene expression, there are two new twists when done in the context of topic modeling:

1. The cluster (topic) assignments are probabilistic.
2. The cluster assignments are made at the level of genes, not cells.

I propose a log-fold change statistic to address these two points. It compares the probability of gene  $j$  occurring ( $w = j$ ) given topic  $k$  ( $z = k$ ) versus the probability given assignment a topic other than  $k$  ( $z \neq k$ ):

$$(11) \quad \text{lfc}^{\text{topics}}(j, k) \equiv \log_2 \frac{p(w = j \mid z = k)}{p(w = j \mid z \neq k)}.$$

For a given gene  $j$  and topic  $k$ ,  $\text{lfc}(j, k)$  can be calculated as

$$(12) \quad \begin{aligned} \text{lfc}^{\text{topics}}(j, k) &= \log_2 \left\{ \frac{p(w = j, z = k)}{p(w = j, z \neq k)} \times \frac{p(z = k)}{p(z \neq k)} \right\} \\ &= \log_2 \left\{ \frac{\sum_{i=1}^n \sum_{t=1}^{s_i} \delta_j(w_{it}) \phi_{ijkt}}{\sum_{i=1}^n \sum_{t=1}^{s_i} \delta_j(w_{it}) (1 - \phi_{ijkt})} \right. \\ &\quad \left. \times \frac{\sum_{i=1}^n \sum_{j'=1}^m \sum_{t=1}^{s_i} \delta_{j'}(w_{it}) (1 - \phi_{ij'kt})}{\sum_{i=1}^n \sum_{j'=1}^m \sum_{t=1}^{s_i} \delta_{j'}(w_{it}) \phi_{ij'kt}} \right\}, \end{aligned}$$

where  $\phi_{ijkt}$  denotes the posterior probability of  $z_{it} = k$  given  $w_{it} = j$ ,

$$(13) \quad \begin{aligned} \phi_{ijkt} &\equiv p(z_{it} = k \mid w_{it} = j) \\ &= \frac{p(w_{it} = j \mid z_{it} = k) p(z_{it} = k)}{\sum_{k'=1}^K p(w_{it} = j \mid z_{it} = k') p(z_{it} = k')} \\ &= \frac{l_{ik} f_{jk}}{\sum_{k'=1}^K l_{ik'} f_{jk'}}. \end{aligned}$$

Since the topic assignments  $z_{it}$  do not depend on  $t$ —that is, we can drop the “ $t$ ” subscript from the  $\phi_{ijk}$ ’s—the expression for the  $lfc$  simplifies:

$$(14) \quad lfc^{\text{topics}}(j, k) = \log_2 \left\{ \frac{\sum_{i=1}^n x_{ij} \phi_{ijk}}{\sum_{i=1}^n x_{ij} (1 - \phi_{ijk})} \times \frac{\sum_{i=1}^n \sum_{j'=1}^m x_{ij'} (1 - \phi_{ij'k})}{\sum_{i=1}^n \sum_{j'=1}^m x_{ij'} \phi_{ij'k}} \right\}.$$

At the maximum-likelihood solution (MLE) of the  $l_{ik}$ ’s and  $f_{jk}$ ’s, the  $lfc$  statistic simplifies further:

$$(15) \quad lfc^{\text{topics}}(j, k) = \log_2 \left\{ \frac{\sum_{i=1}^n x_{ij} \phi_{ijk}}{\sum_{i=1}^n x_{ij} (1 - \phi_{ijk})} \times \frac{\sum_{i=1}^n s_i (1 - l_{ik})}{\sum_{i=1}^n s_i l_{ik}} \right\}.$$

This is because, at the MLE, the loadings  $l_{ik}$ ,  $k = 1, \dots, K$ , for a given document/cell  $i$  should be equal to the average of the weighted counts  $\frac{1}{s_i} \sum_{j=1}^m x_{ij} \phi_{ijk}$ .

Finally, it is convenient that the  $lfc$  (11, 14) will be the same if we replace the multinomial topic model parameters  $l_{ik}$  and  $f_{jk}$  with the corresponding parameters of the Poisson NMF,  $\hat{l}_{ik}$  and  $\hat{f}_{jk}$  (proof not given). From the derivation of the EM algorithm for Poisson NMF, this identity holds at the MLE:

$$\hat{f}_{jk} = \frac{\sum_{i=1}^n \phi_{ijk}}{\sum_{i=1}^n \hat{l}_{ik}}.$$

Plugging this relationship into (14), we obtain the following simple expression for the log-fold change:

$$(16) \quad lfc^{\text{topics}}(j, k) = \log_2 \left\{ \frac{\hat{f}_{jk} \sum_{i=1}^n \hat{l}_{ik}}{\sum_{k' \neq k} \hat{f}_{jk'} \sum_{i=1}^n \hat{l}_{ik'}} \times \frac{\sum_{i=1}^n s_i (1 - \hat{l}_{ik})}{\sum_{i=1}^n s_i \hat{l}_{ik}} \right\}.$$

What is nice about this about this expression is that it can be computed without seeing the data. It is also plain to see from this expression that to arrive at a log-fold change, one must weight the factors  $f_{jk}$  by the sample-wide topic probabilities  $\sum_i l_{ik}$  across This same expression also works with the for the parameters of multinomial topic model  $l_{ik}$ ,  $f_{jk}$ , again, so long as they are MLEs (proof not shown).

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