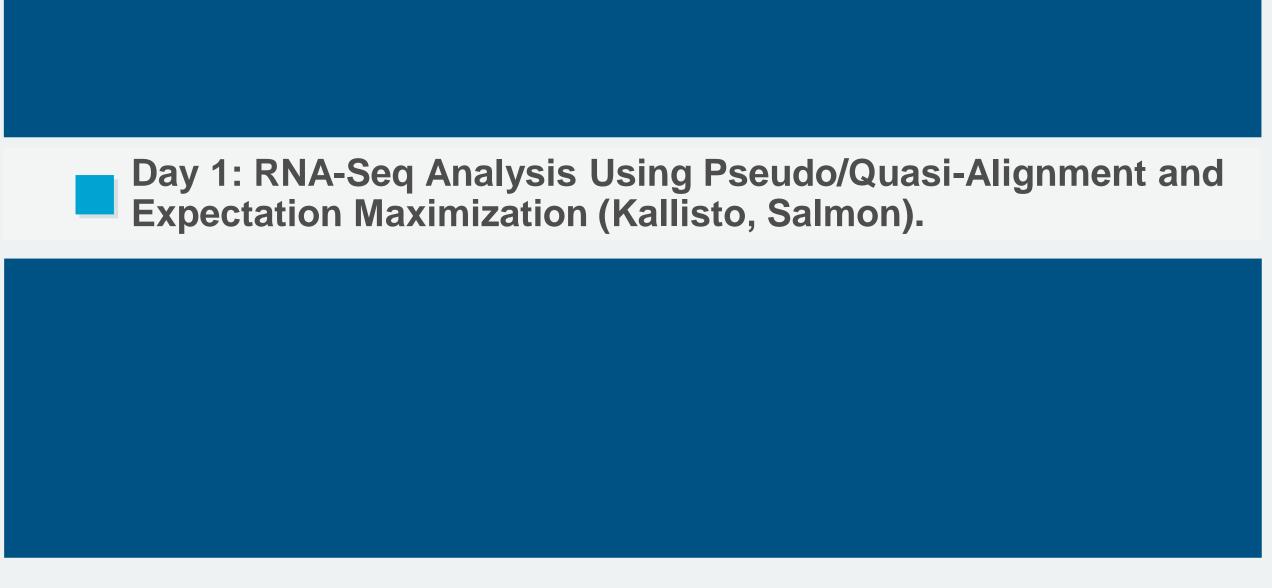
Advanced NGS Analysis (Day 1) Session II

Lyda Hill department of Bioinformatics 2022 Nanocourse Series

Date & Time: June 27-28: 9AM-5PM (NB2.100A)

Course Instructors: Bo Li, Daehwan Kim, Christopher Chaney, & Micah Thornton (micah.Thornton@utsouthwestern.edu)

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Part 1: Pseudo and Quasi Alignment & Quantification Resolution



RNA-Seq Experiments (Key Difference from DNA)

- In DNA-Seq, we usually align 'NGS sequencing reads' to a reference genome.
 - These sequences include all exons and introns, in fixed order.



- In RNA-Seq on the other hand we might try to align to a 'transcriptome'.
 - These include a set of 'transcripts' which contain different possible sequences encoded by the same gene





RNA-Seq Experiments (Key Questions)

- In RNA-Seq experiments researchers hope to answer questions such as:
 - 1. How do abundances of a particular gene transcripts in the same population vary?
 - Ex. Do subjects with a high abundance of transcript A, tend also to exhibit relatively high abundances of transcript B?
 - 2. Do the abundances of gene transcripts vary with some observable phenotypic characteristic?
 - Ex. Do patients with latent state tuberculosis exhibit more abundance of transcript A than those with active state?
 - 3. What constitutes the most likely genetic transcript profile for a particular subject?
 - Ex. Is Transcript A more abundant in this subject?
 - 4. Etc ...
- So if we do not have exact *positional* alignments for reads, that is okay, as long as we are able to determine the most likely transcript that they came from. (Expectation Maximization for Multinomial Data)



- In some RNA-Seq Experiments the *actual* alignment of reads may not be measurable in some cases.
- For instance, consider the following small example,

- It is possible that many RNA-Seq reads might be compatible with the same transcripts.
- Therefore for each of the RNA-Seq reads, the actual alignment is not directly recoverable.



Sequencing Reads

- Instead of working directly with the sequences to produce *positional* alignments (the exact position where the read came from), coarsened compatibility patterns may be observed for the transcripts the read is compatible with.
- From the previous example,



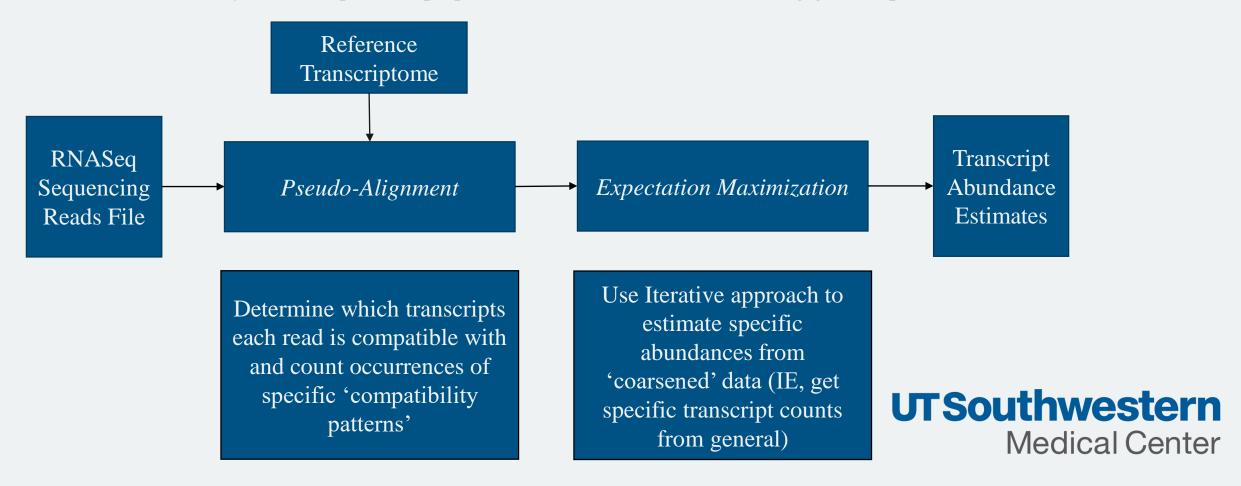
- Instead of working directly with the sequences to produce *positional* alignments (the exact position where the read came from), coarsened compatibility patterns may be observed for the transcripts the read is compatible with.
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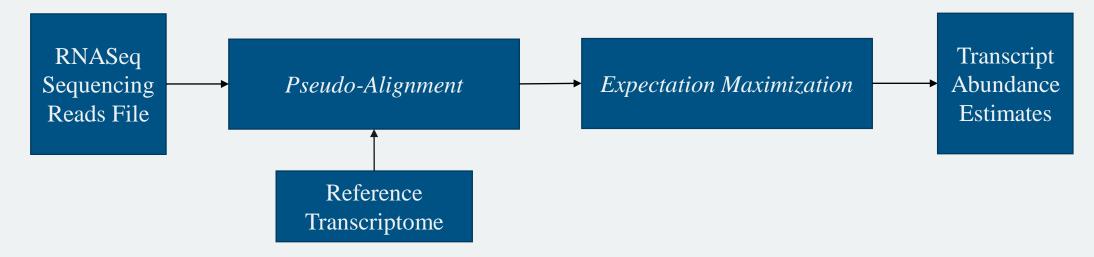
Sequencing Reads Transcript Compatibility Pattern

Transcript 1	ACCCCGAGAGTTAGAGCGTGTGAGAGAA	GAGTTA	100
Transcript 2	ACCCCGAGAGGGAAGAGACTTTAGAGCGT	GACTTT	011 101
Transcript 3	GGAAGAGACTTTAGAGCGTGTGAGAGAA	GAGCGT	111



- Now suppose that there are 10 Million such reads aligning to the transcriptome.
- Since *positional* alignment information may not allow the discernment of transcripts,
 - Not necessary to determine and report such information.
- Instead, many RNA-Seq transcript quantification tools use the following general procedure:





- First data is collected from the RNA of the subject(s) under study using NGS technologies (short read sequencing)
- Compatibility for each read with each transcript in a *Reference Transcriptome* is determined by some Pseudo-Alignment procedure.
- Expectation Maximization for abundances of the true transcript counts X_i are determined from the coarsened pattern counts Y_i .
- Estimates of the parameters of the distribution of Y_i (for $i = 1, ..., N_t$), γ_i , are presented as abundance estimates, and multiplied by the number of reads N_r for expectations.



RNA-Seq Abundance Estimation: Kallisto

- First data is collected from the RNA of the subject(s) under study using NGS technologies (short read sequencing)
- Compatibility for each read with each transcript in a *Reference Transcriptome* is determined by some Pseudo-Alignment procedure.
- Expectation Maximization for abundances of the true transcript counts X_i are determined from the coarsened pattern counts Y_i .
- Estimates of the parameters of the distribution of Y_i (for $i = 1, ..., N_t$), γ_i , are presented as abundance estimates, and multiplied by the number of reads N_r for expectations.
- Sometimes TPM (Transcripts per million reads) are also presented.
- Two popular procedures which implement this approach are Salmon and Kallisto.
 - These will be presented and a demonstration given.

Tomorrow we will walk through installation of these software and their usage, and a third software will

be demonstrated*.



Salmon

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Lyss

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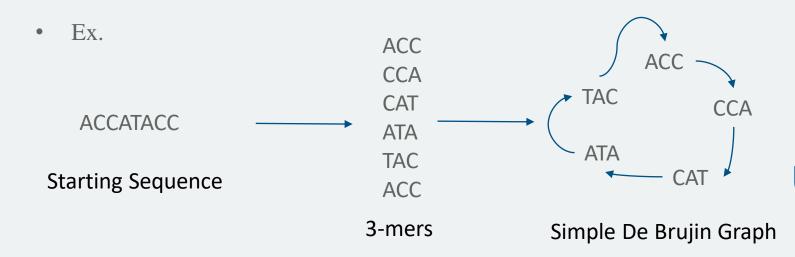
Kallisto

* we are creating a new tool called H2Q which takes into account SNP variability between alleles to provide allele specific transcript quantification results



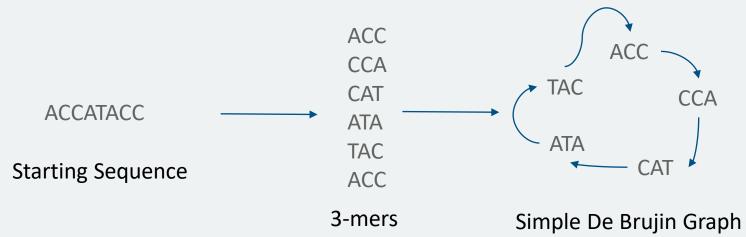
Kallisto: Understanding the Algorithm

- As previously stated, the RNA-Seq quantification algorithms used in state of the art applications generally follow two steps:
 - 1. "Pseudo-Alignments" indicating the subset of transcripts which are 'compatible' with each read are determined.
 - 2. The Expectation Maximization algorithm is applied to determine the Maximum Likelihood Estimators for the Multinomial Proportions associated with each transcript.
- Kallisto uses a transcriptome de Brujin graph to determine which transcripts are compatible with each read (pair).
 - The De Brujin Graph represents sequences by connecting nodes of subsequences (in this case we call them k-mers, where k denotes the size.

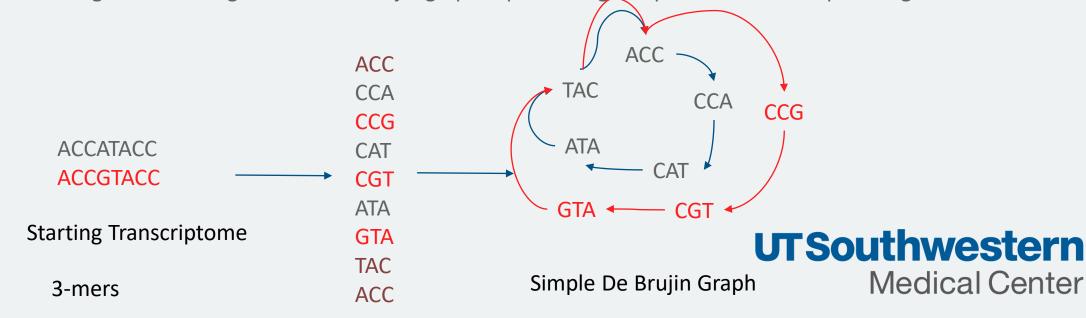




Kallisto: Understanding the Algorithm (Pseudo-Alignment)

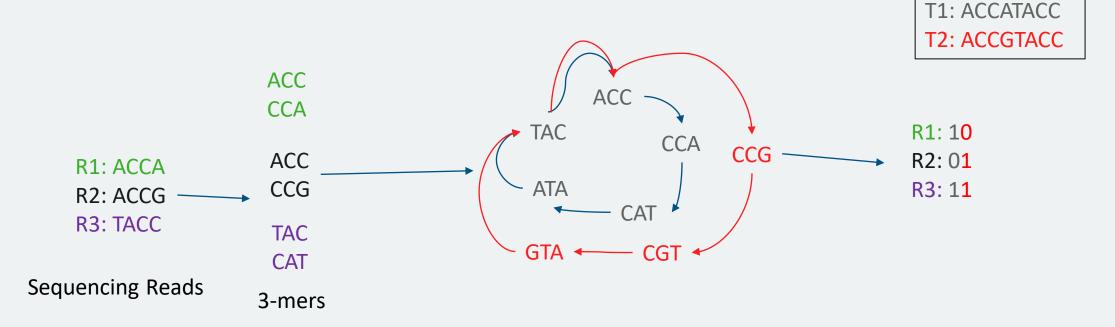


• Extending the De Brujin procedure to representing transcriptomes can be accomplished by adding "colors" or categorical weights to the edges of the De Brujin graph representing the particular transcript of alignment.



Kallisto: Understanding the Algorithm (Pseudo-Alignment)

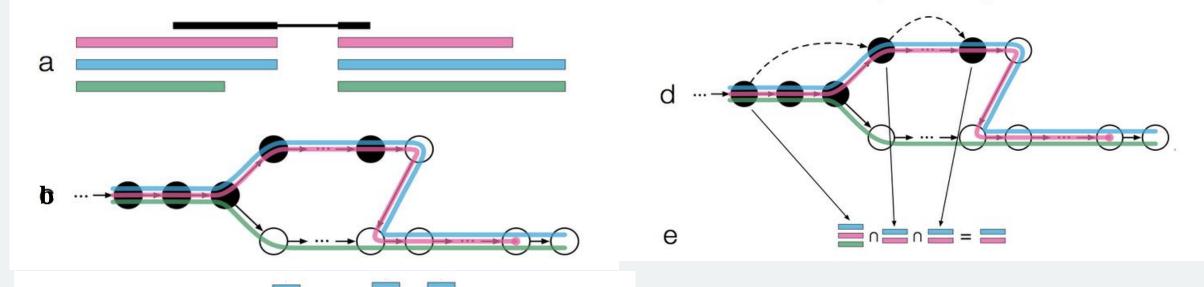
• Given a new set of reads, the *k*-mers can be determined, and then using the De Brujin Graph Transcriptome, the *pseudo*-alignments of a set of reads can be determined.

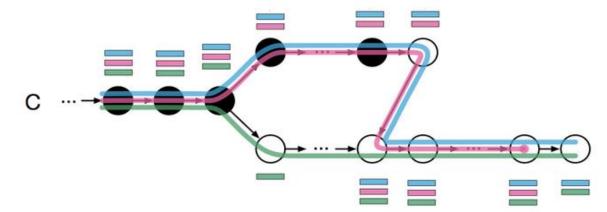


Comparison of 3-mers from reads to color DBG transcriptome allows the determination of compatibility counts.



Kallisto Pseudo-Alignment Example Backup





This is taken from Fong Chun Chan's Blog post on "How Pseudoalignments Work in Kallisto."

https://tinyheero.github.io/2015/09/02/pseudoalig nments-kallisto.html



Salmon: Understanding the Algorithm (Quasi-Mapping)

$$\Pr\{f_j|t_i\} = \Pr\{\ell|t_i\} \cdot \Pr\{p|t_i,\ell\} \cdot \Pr\{o|t_i\} \cdot \Pr\{a|f_j,t_i,p,o,\ell\}$$

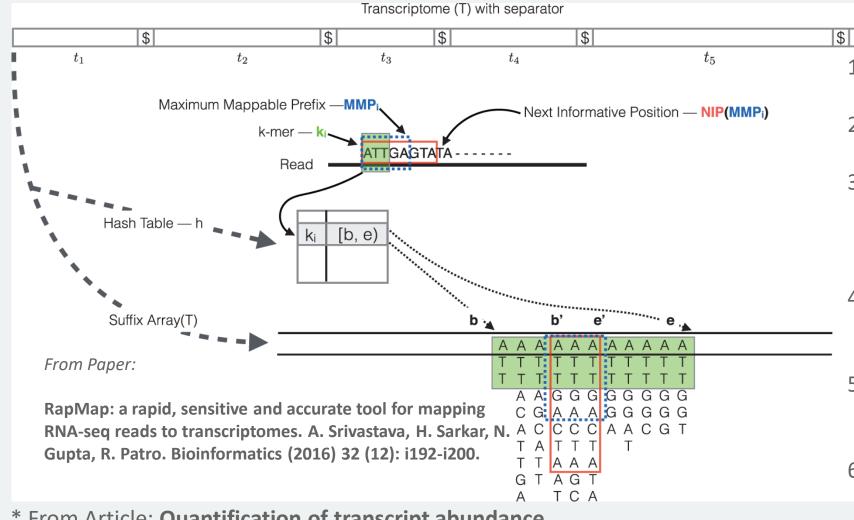
Equation 6

- If alignments are being used, then the Fragment-Transcript agreement model used by Salmon incorporates the true alignment information in this term (The Probability of generating alignment a of fragment f_i , being drawn from t_i , with position, orientation, and length, p, o, ℓ .
- In 'Quasi-Mapping' Mode however this term is fixed as 1.
- In Salmon, there are additional phases where parameters are calculated and utilized for determining a better transcript abundance quantification.

Patro R, Duggal G, Love MI, Irizarry RA, Kingsford C. Salmon provides fast and bias-aware quantification of transcript expression. *Nat Methods*. 2017;14(4):417-419. doi:10.1038/nmeth.4197



Salmon: Understanding the Algorithm (Quasi-Mapping)



^{*} From Article: Quantification of transcript abundance using Salmon Introduction to bulk RNA-seq

https://hbctraining.github.io/Intro-to-rnaseq-hpc-salmonflipped/lessons/08 quasi alignment_salmon.html

- 1. ^{t₆} First a Suffix Array is built for the transcriptome
- 2. A K-mer Hash table for indexing into the the suffix array is constructed
- 3. Reads are scanned, and when k-mers in the hash table are found, all suffixes matching are extracted from the suffix array
- 4. The longest prefix in common among all the suffixes (called the MMP Maximal Matching Prefix) is found.
- This is repeated for all kmers, and then the intersection of transcripts in the MMP
- 6. The Transcripts which are intersected by the associated MMP are provided as the compatible quasi-mappings

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Questions about Pseudo-Alignment/Quasi-Mapping?



Break (10 Minutes)



Part 2: Expectation Maximization & Gene Transcript Quantification



Pseudo/Quasi Alignment in RNA Experiments

- Sometimes the *exact* position of a sequencing read is not of critical import.
 - There are a few approaches for resolving the *approximate* location of a read.
 - Procedures work by determining the subset of *transcript isoforms* compatible with a read.
 - Two such approaches are known as:
 - Pseudo-Alignment
 - The Approach used by Kallisto.
 - Uses the De Brujin ('Deh-Broine') graph procedure.
 - Quasi-Alignment
 - The Approach used by **Salmon.**
 - Uses a *K*-mer Hash table and Suffix Array.

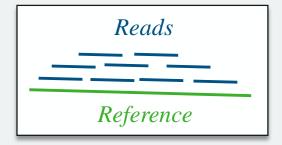
Resources - Kallisto (Pseudo-alignment)

- 1. https://tinyheero.github.io/2015/09/02/pseudoalignments-kallisto.html (Higher Level Overview pseudo alignment)
- 2. https://www.youtube.com/watch?v=f-ecmECK7lw (Video Describing how To Build The De Brujin graph)
- 3. https://www.nature.com/articles/nbt.2023 (Nature Primer on Using De Brujin Graphs for Genomic Alignments).

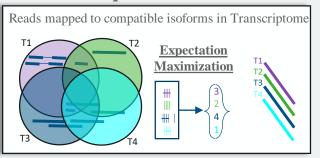
<u>Resources – Salmon (Quasi-alignment)</u>

- 1. https://hbctraining.github.io/Intro-to-rnaseq-hpc-salmon-flipped/lessons/08 quasi alignment salmon.html (Higher Level Overview Quasi-Alignment)
- 2. https://academic.oup.com/bioinformatics/article/32/12/i192/2288985?login=true (RapMap Paper and Description).

Typical 'DNA-Seq Like' Experiment



Typical 'RNA-Seq Like' Experiment



Recall that in most typical sequencing experiments we are dealing with a large collection of shorter subsequences called *reads*, which we attempt to map to a larger sequence known as the *reference*.

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Expectation Maximization (in general) – Incomplete Data & A Restricted Case

- Many-to-one relationship
- X Y

- Two general uses include:
 - determination of maximum likelihood estimates for parameters when missing data is present and
 - estimation of missing or otherwise incomplete data.
- In general, suppose that we would like to observe the values, $x_1, x_2, ... x_n$, to determine something about the parameters of the random variable X which has sample space X as shown (top right).
 - However, we are only able to observe, $y_1, y_2, ... y_n$, valuations of the random variable Y which has sample space \mathcal{Y} onto which there exists a many-to-one mapping from \mathcal{X} .
 - In other words, there are multiple values possible to observe in \mathcal{X} corresponding to the same value in \mathcal{Y} .
- Suppose, at first, that the distribution of *X* (note boldface indicates that *X* could be a vector quantity) is one of the exponential family of distributions generally denoted,

$$f_X(x|\boldsymbol{\theta}) = b(x)e^{(\boldsymbol{\theta}t(x)^T)}a(\boldsymbol{\theta})^{-1}$$

 θ is a parameter [column]-vector (of size r). $t(x)^T$ is the sufficient statistic [row]-vector (of size r). $a(\cdot), b(\cdot)$, are any arbitrary function. e is the natural number.

See section II of the Dempster, Laird, Rubin paper mentioned below for more details about natural parameters.

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These Expectation Maximization Notes Draw Heavily from "Maximum Likelihood from Incomplete Data via the EM Algorithm" by Dempster Rubin and Laird (https://www.jstor.org/stable/2984875)

Expectation Maximization (in general) – The Algorithm

- The "simple characterization" of the EM algorithm according to Dempster, Laird, and Rubin (DLR77) is:
 - (1) With $\theta^{(p)}$ indicating the estimate of θ at the p^{th} step of the algorithm, estimate the complete-data sufficient statistics t(x) by finding

$$\mathbf{t}^{(p)} = E(\mathbf{t}(\mathbf{x})|\mathbf{y}, \boldsymbol{\theta}^{(p)}).$$

(2) Perform maximum likelihood estimation to determine $\theta^{(p+1)}$ from $t^{(p)}$,

$$E(t(x)|\theta)=t^{(p)}.$$

- Proof of convergence to the maximum likelihood value is given the DLR77, as are details regarding further generalizations of the expectation maximization algorithm.
- The algorithm is broadly applicable in many cases, and not all of the applications have been discovered yet.

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Expectation Maximization (in general) – A Multinomial Example

- Suppose that there are marbles of five colors in a bag.
 - Red marbles are denoted by 'R'
 - Orange marbles are denoted by 'O'
 - Yellow marbles by 'Y'
 - Green marbles by 'G'
 - Blue marbles by 'B'
- Now, you personally cannot tell a difference between the orange and the yellow marbles by eye, and therefore are able to produce counts of four categories of marbles only (that is: "Red", "Orange or Yellow", "Green", and "Blue").

[EXAMPLE]

• Suppose it is known ahead of time that the proportions of the *actual* colors of each of the marbles are related via an unknown parameter π , such that for the unobservable true color of an arbitrarily selected marble i, denoted c_i (true color) given below induces a distribution on the observable o_i (observed color) follows this distribution:

$$P\left(\begin{array}{c} \operatorname{Red} \\ \operatorname{Orange} \\ \operatorname{Yellow} \\ \operatorname{Green} \\ \operatorname{Blue} \end{array}\right) = \begin{pmatrix} (1-\pi)/4 \\ \pi/4 \\ 1/2 \\ (1-\pi)/4 \\ \pi/4 \end{pmatrix} \Rightarrow P\left(\begin{array}{c} \operatorname{Red} \\ \operatorname{Orange or Yellow} \\ \operatorname{Green} \\ \operatorname{Blue} \end{array}\right) = \begin{pmatrix} (1-\pi)/4 \\ 1/2 + \pi/4 \\ (1-\pi)/4 \\ \pi/4 \end{pmatrix}$$

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These Expectation Maximization Notes Draw Heavily from "Maximum Likelihood from Incomplete Data via the EM Algorithm" by Dempster Rubin and Laird (https://www.jstor.org/stable/2984875)

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Orange or

Yellow

- Green

→ Blue

Orange

Yellow

Green

Expectation Maximization (in general) – A Multinomial Example (Continued)

Suppose that we observe 197 marbles, and arrive at the following counts:

B – Blue: 34

$$P\left(\begin{array}{c} \text{Red} \\ \text{Orange} \\ \text{Yellow} \\ \text{Green} \\ \text{Blue} \end{array}\right) = \begin{pmatrix} (1-\pi)/4 \\ \pi/4 \\ 1/2 \\ (1-\pi)/4 \\ \pi/4 \end{pmatrix} \Rightarrow P\left(\begin{array}{c} \text{Red} \\ \text{Orange or Yellow} \\ \text{Green} \\ \text{Blue} \end{array}\right) = \begin{pmatrix} (1-\pi)/4 \\ 1/2 + \pi/4 \\ (1-\pi)/4 \\ \pi/4 \end{pmatrix}$$

G-Green: 20
$$B - Blue: 34$$

$$x_{j} = \sum_{i=1}^{197} \mathbb{1}(c_{i} \equiv j)$$

$$j \in \begin{pmatrix} Red \\ Orange \\ Yellow \\ Green \\ Blue \end{pmatrix}$$

$$y_{t} = \sum_{i=1}^{197} \mathbb{1}(o_{i} \equiv t)$$

$$t \in \begin{pmatrix} Red \\ Orange \\ Orange$$

- Let the *actual* color counts be denoted by the values $(x_1, x_2, x_3, x_4, x_5)$ such that x_1 corresponds to the count of marbles which were actually red, x_2 to those which were Orange, and so on...
- Let the observed color counts be denoted by the values (y_1, y_2, y_3, y_4) which are given in this example as (18,125,20,34).

• Furthermore, it is known that $y_2 = x_2 + x_3$.

- The Likelihood on π for the full data can be expressed as:
 - $f(x|\pi) = \frac{\left(\sum_{i=1}^{5} x_i\right)!}{\prod_{i=1}^{5} (x_i!)} \cdot \left(\frac{1-\pi}{4}\right)^{x_1} \cdot \left(\frac{\pi}{4}\right)^{x_2} \cdot \left(\frac{1}{2}\right)^{x_3} \cdot \left(\frac{1-\pi}{4}\right)^{x_4} \cdot \left(\frac{\pi}{4}\right)^{x_5}$
- The *coarsened/incomplete* Likelihood on π for the full data can be expressed as:

 $g(\mathbf{y}|\pi) = \frac{\left(\sum_{i=1}^{4} y_{i}\right)!}{\prod_{i=1}^{4} (y_{i}!)} \cdot \left(1 - \frac{\pi}{4}\right)^{y_{1}} \cdot \left(\frac{1}{2} + \frac{\pi}{4}\right)^{y_{2}} \cdot \left(1 - \frac{\pi}{4}\right)^{y_{3}} \cdot \left(\frac{\pi}{4}\right)^{y_{4}} \cdot \left(\frac{\pi}{4}\right)^{y_{4}}$ Medical Center DLR77 (https://www.jstor.org/stable/298487

Expectation Maximization (in general) – A Multinomial Example (E-Step)

Clearly, due to the fact that a marble cannot *actually* be two colors simultaneously, there is no probability that any marble is *truly* both orange and yellow at the same time, therefore we may express the probability that a marble is orange or yellow as follows:

$$P(o_i = (\text{Orange or Yellow})) = P(c_i \in (\text{Orange})) = P(c_i = \text{Orange}) + P(c_i = \text{Yellow}) - P(c_i = \text{Yellow}) - P(c_i = \text{Yellow}) = P(c_i = \text{Orange}) + P(c_i = \text{Yellow}) - P(c_i = \text{Yell$$

From here we can derive the expression for the maximum likelihood estimates of the unobserved counts for orange and yellow marbles (x_2, x_3) in terms of the observed count of "orange or yellow" marbles (y_2) .

$$P(c_{i} = \text{Orange } | o_{i} = (\text{Orange or Yellow})) = \frac{P(o_{i} = (\text{Orange or Yellow}) \& c_{i} = \text{Orange})}{\frac{1}{2}} = \frac{P(c_{i} = \text{Orange})}{P(o_{i} = (\text{Orange or Yellow}))} = \frac{\frac{\pi}{4}}{\frac{\pi}{4} + \frac{1}{2}}$$

$$P(c_{i} = \text{Yellow } | o_{i} = (\text{Orange or Yellow})) = \frac{\frac{\pi}{4}}{\frac{\pi}{4} + \frac{1}{2}}$$
Therefore the conditional expectation of x_{2} and x_{3} are x_{3} and x_{4} and x_{5} are x_{5} .

$$P(c_i = \text{Yellow} | o_i = (\text{Orange or Yellow})) = \frac{\overline{2}}{\frac{\pi}{4} + \frac{1}{2}}$$

Therefore the conditional expectation of x_2 and x_3 are:

 $E(x_2|y_2) = y_2 \frac{\frac{\pi}{4}}{\frac{\pi}{4} + \frac{1}{2}}$ - and - $E(x_3|y_2) = y_2 \frac{\frac{1}{2}}{\frac{\pi}{4} + \frac{1}{2}}$

Suppose that we observe 197 marbles, and arrive at the following counts:

R-Red: 18 OY—Orange or Yellow:125 G-Green: 20 B - Blue: 34

These Expectation Maximization Notes Draw Heavily from "Maximum Likelihood from Incomplete Data via the EM Algorithm" by Dempster Rubin and Laird (https://www.istor.org/stable/2984875)



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Expectation Maximization (in general) – A Multinomial Example (M-Step)

 $\Rightarrow x_1 + x_4 = x_2 \hat{\pi} + x_5 \hat{\pi} + x_1 \hat{\pi} + x_4 \hat{\pi}$

Recall that the full likelihood for the multinomial distribution was given by:

$$f(x|\pi) = \frac{\left(\sum_{i=1}^{5} x_i\right)!}{\prod_{i=1}^{5} (x_i!)} \cdot \left(\frac{1-\pi}{4}\right)^{x_1} \cdot \left(\frac{\pi}{4}\right)^{x_2} \cdot \left(\frac{1}{2}\right)^{x_3} \cdot \left(\frac{1-\pi}{4}\right)^{x_4} \cdot \left(\frac{\pi}{4}\right)^{x_5}$$

$$\Rightarrow \log L(\pi|\mathbf{x}) = \log \frac{\left(\sum_{i=1}^{5} x_i\right)!}{\prod_{i=1}^{5} (x_i!)} + x_1 \log \left(\frac{(1-\pi)}{4}\right) + x_2 \log \left(\frac{\pi}{4}\right) + x_3 \log \left(\frac{1}{2}\right) + x_4 \log \left(\frac{(1-\pi)}{4}\right) + x_5 \log \left(\frac{\pi}{4}\right)$$

In this example, only x_2 and x_3 are unobservable, the rest are known:

$$\Rightarrow \frac{\partial \log L(\pi|x)}{\partial \pi} = x_1 \left(\frac{4}{1-\pi}\right) \left(-\frac{1}{4}\right) + x_2 \left(\frac{4}{\pi}\right) \left(\frac{1}{4}\right) + x_4 \left(\frac{4}{1-\pi}\right) \left(-\frac{1}{4}\right) + x_5 \left(\frac{4}{\pi}\right) \left(\frac{1}{4}\right) = \frac{x_1}{\pi - 1} + \frac{x_2}{\pi} + \frac{x_4}{\pi - 1} + \frac{x_5}{\pi}$$

$$\Rightarrow \frac{x_1}{\hat{\pi} - 1} + \frac{x_2}{\hat{\pi}} + \frac{x_4}{\hat{\pi} - 1} + \frac{x_5}{\hat{\pi}} = 0 \Rightarrow (x_2 + x_5)(1 - \hat{\pi}) = (x_1 + x_4)\hat{\pi} \Rightarrow x_2 + x_5 - x_2\hat{\pi} - x_5\hat{\pi} = x_1\hat{\pi} + x_4\hat{\pi}$$

$$\Rightarrow x_2 + x_5 = (x_1 + x_2 + x_4 + x_5)\hat{\pi} \Rightarrow \hat{\pi} = \frac{(x_2 + x_5)}{x_1 + x_2 + x_4 + x_5} \Rightarrow -x_1\hat{\pi} - x_4\hat{\pi} + x_4 = x_3\hat{\pi} + x_5$$

$$\Rightarrow -x_1\hat{\pi} - x_4\hat{\pi} + x_4 = x_3\hat{\pi} + x_5$$

Suppose that we observe 197 marbles, and arrive at the following counts:

$$\begin{pmatrix} x_1 \\ x_4 \\ x_5 \end{pmatrix} = \begin{pmatrix} 18 \\ 20 \\ 34 \end{pmatrix} \Rightarrow \hat{\pi} = \frac{x_2 + 34}{18 + x_2 + 20 + 34}$$

 $\Rightarrow -x_1\hat{\pi} - x_4\hat{\pi} + x_1 + x_4 = x_2\hat{\pi} + x_5\hat{\pi}$

Suppose that we observe 197 marbles, and arrive at the following counts:
$$\begin{pmatrix} x_1 \\ x_4 \\ x_5 \end{pmatrix} = \begin{pmatrix} 18 \\ 20 \\ 34 \end{pmatrix} \Rightarrow \hat{\pi} = \frac{x_2 + 34}{18 + x_2 + 20 + 34}$$

$$\Rightarrow x_1 + x_4 = x_2 \hat{\pi} + x_5 \hat{\pi} + x_1 \hat{\pi} + x_4 \hat{\pi}$$

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$$\Rightarrow x_1 + x_2 = x_2 \hat{\pi} + x_3 \hat{\pi}$$

$$\Rightarrow x_1 + x_2 = x_3 \hat{\pi} + x_3 \hat{\pi}$$

$$\Rightarrow x_1 + x_2 = x_3 \hat{\pi} + x_3 \hat{\pi}$$

$$\Rightarrow x_1 + x_2 = x_3 \hat{\pi} + x_3 \hat{\pi}$$

$$\Rightarrow x_1 + x_2 = x_3 \hat{\pi} + x_3 \hat{\pi}$$

$$\Rightarrow x_1 + x_2 = x_3 \hat{\pi} + x_3 \hat{\pi}$$

$$\Rightarrow x_1 + x_2 = x_3 \hat{\pi} + x_3 \hat{\pi}$$

$$\Rightarrow x_1 + x_2 = x_3 \hat{\pi} + x_3 \hat{\pi}$$

$$\Rightarrow x_1 + x_2 = x_3 \hat{\pi} + x_3 \hat{\pi}$$

$$\Rightarrow x_1 + x_2 = x_3 \hat{\pi} + x_3 \hat{\pi}$$

$$\Rightarrow x_1 + x_2 = x_3 \hat{\pi} + x_3 \hat{\pi}$$

$$\Rightarrow x_1 + x_2 = x_3 \hat{\pi} + x_3 \hat{\pi}$$

$$\Rightarrow x_1 + x_2 + x_3 \hat{\pi} + x_3 \hat{\pi} + x_3 \hat{\pi}$$

$$\Rightarrow x_1 + x_2 + x_3 \hat{\pi} + x_3 \hat{\pi} + x_3 \hat{\pi} + x_3 \hat{\pi}$$

Expectation Maximization (in general) – A Multinomial Example (Iteration)

• Taking the conditional expectations for the computation of x_2 and x_3 will depend on a particular estimation of π , an initial estimate $(\pi^{(0)})$ must be supplied to the algorithm to start the procedure, then conditional expectations for the missing (coarsened) data at the p^{th} step (where $p \in \{1,2,...\}$) is given by:

[E-Step]
$$E_{(p)}(x_2|y_2) = y_2 \frac{\frac{\pi^{(p-1)}}{4}}{\frac{\pi^{(p-1)}}{4} + \frac{1}{2}} \text{ and } E_{(p)}(x_3|y_2) = y_2 \frac{\frac{1}{2}}{\frac{\pi^{(p-1)}}{4} + \frac{1}{2}}$$

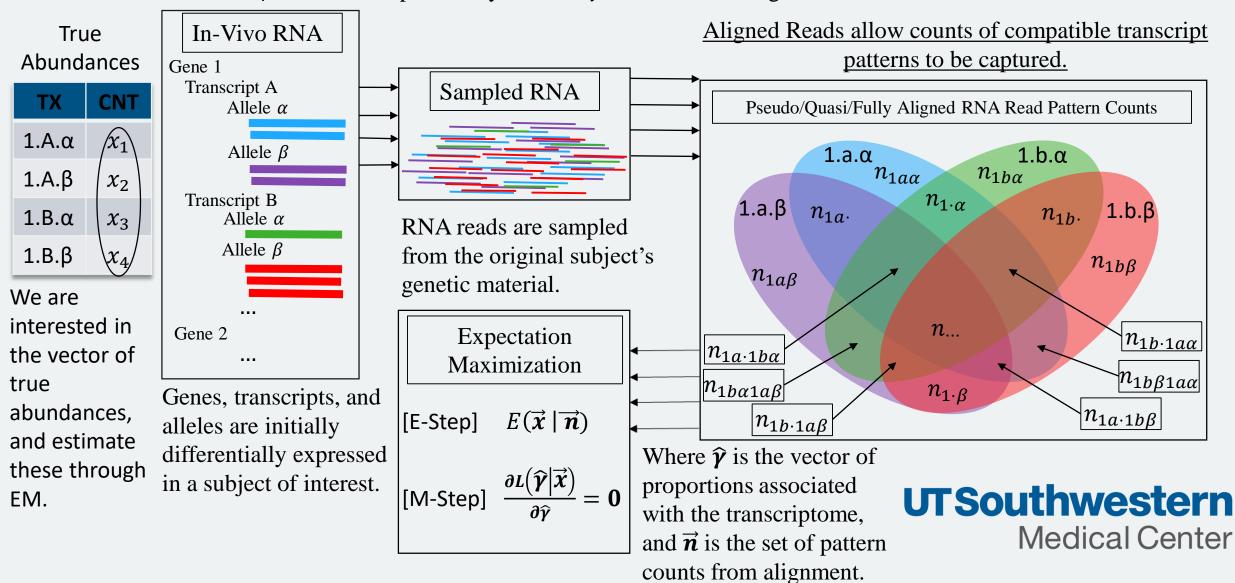
[M - Step]
$$\widehat{\pi^{(p)}} = \frac{1}{1 + \frac{38}{E_{(p)}(x_2|y_2) + 34}}$$

- Convergence Criteria:
 - Generally we use relative convergence criteria (when the change in the parameters from step p to step p+1 falls below a relative tolerance ε_R) to determine when to stop iterating, for instance, the iteration will continue until:

[Convergence]
$$\left(\frac{1}{1 + \frac{38}{E_{(p)}(x_2|y_2) + 34}} - \frac{1}{1 + \frac{38}{E_{(p-1)}(x_2|y_2) + 34}}\right)^2 \le \varepsilon_R$$
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Expectation Maximization (Genetic Abundance Estimation)

- We observe N_r RNA-seq reads from an experiment involving a transcriptome of size T.
 - Each of the N_r reads came specifically from *only* one of the T categories.



Expectation Maximization (Genetic Abundance Estimation) [M-Step]

- Clearly, the distribution of the reads among their true transcript sources can be modeled as multinomial.
 - The probability distribution of the count vector of the true abundances, \vec{X} , is

$$\Pr(\overrightarrow{X} = \overrightarrow{x}) = \frac{\left(\sum_{i=1}^{N} x_i\right)!}{\prod_{i=1}^{N} (x_i)!} \prod_{i=1}^{N} \gamma_i^{x_i}$$

This probability distribution function doubles as the Likelihood for the parameter vector $\vec{\gamma}$ under the observed data \vec{x} .

$$L(\vec{\gamma}|\vec{x}) = \frac{\left(\sum_{i=1}^{N} x_i\right)!}{\prod_{i=1}^{N} (x_i)!} \prod_{i=1}^{N} \gamma_i^{x_i} \Rightarrow \ell(\vec{\gamma}|\vec{x}) = \log \frac{\left(\sum_{i=1}^{N} x_i\right)!}{\prod_{i=1}^{N} (x_i)!} + \sum_{i=1}^{N} x_i \log \gamma_i \Rightarrow \frac{\partial \ell(\vec{\gamma}|\vec{x})}{\partial \gamma_i} = \frac{x_i}{\gamma_i}$$

$$\sum_{i=1}^{N} \gamma_i = 1$$

- Do not forget that there is an inherent constraint on the parameter space (the sum of all proportions must be one).
 - We must optimize $\ell(\vec{\gamma}|\vec{x})$ subject to the constraint: $\sum_{i=1}^{N} \gamma_i = 1$.
 - This is accomplished by using the method of Lagrange multipliers.

$$\ell'(\overrightarrow{\boldsymbol{\gamma}},\lambda) = \ell(\overrightarrow{\boldsymbol{\gamma}}) + \lambda \left(1 - \sum_{i=1}^{N} \gamma_i\right) \Rightarrow \frac{\partial \ell'(\overrightarrow{\boldsymbol{\gamma}},\lambda)}{\partial \gamma_i} = \frac{x_i}{\gamma_i} - \lambda \Rightarrow \frac{x_i}{\widehat{\gamma_i}} - \lambda = 0 \Rightarrow \widehat{\gamma_i} = \frac{x_i}{\lambda}$$

$$\widehat{\gamma_i} = \frac{x_i}{\lambda} \Rightarrow \sum_{i=1}^{N} \frac{x_i}{\lambda} = 1 \Rightarrow \frac{1}{\lambda} \sum_{i=1}^{N} x_i = 1 \Rightarrow \lambda = \sum_{i=1}^{N} x_i = N_r \Rightarrow \widehat{\gamma_i} = \frac{x_i}{N_r}$$
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Expectation Maximization (Genetic Abundance Estimation) [E-Step]

- The algorithm calculates the conditional expectation for missing x_i values during the E-Step.
 - If x_i is missing, we must first determine a valid estimate of x_i using the parameter estimated from the previous step (or the initial value used).
 - Instead of observing the vector \vec{x} directly, we observe the pattern count vector \vec{n} .
 - Let the elements of \vec{n} , $(n_1, n_2, ..., n_{N_k})$ be indexed by j, which runs from 1 to the number of unique compatibility patterns (N_k) .
 - The conditional expectations of the missing components of \vec{x} are computed using the elements of \vec{n} , which compose the counts of patterns including those same missing components.
 - For example, if x_1 is missing, but we determine there are reads which align to x_1 as well as others, say n_1 , n_3 , and, n_5 are compatible with transcript 1, then each of these quantities would be used to compute the conditional expectation of the missing value.
 - Note, we either begin with $\gamma^{(0)}$, or have iterated to the p^{th} step, and have $\gamma^{(p-1)}$.
 - The conditional expectation of the missing value, x_i , is determined by considering the observations of those elements of \vec{n} which contain alignments to transcript i.
 - Let the indicator ψ_{ij} be 1 if read i is present in compatibility pattern j and 0 otherwise.

$$E_{(p)}(x_i \mid \vec{n}) = \frac{\gamma_i^{(p-1)}}{\sum_{j=1}^{N_p} \psi_{ij} n_j \gamma_i^{(p-1)}} N_r$$



Expectation Maximization (Genetic Abundance Estimation)

• The EM algorithm amounts to applying these two operations in alternative order until there is convergence in the parameter vector.

[E-Step]
$$E_{(p)}(x_i \mid \vec{\boldsymbol{n}}) = \frac{\widehat{\gamma_i^{(p-1)}}}{\sum_{i=1}^{N_k} \psi_{ij} n_i \widehat{\gamma_i^{(p-1)}}} n_j$$
 [M-Step] $\widehat{\gamma_i}^{(p)} = \frac{E_{(p)}(x_i \mid \vec{\boldsymbol{n}})}{N_r}$

• The EM Algorithm will achieve convergence when the change from step p-1 to p is below some user selected relative tolerance ε_r .

[Convergence Criteria]
$$\widehat{\gamma}_i^{(p)} - \widehat{\gamma}_i^{(p-1)} \le \varepsilon_r$$

• Note the Expectation Maximization algorithm for Multinomial count data (as above) can be applied in a general case. This algorithm is implemented in multiple software packages available for use, but we have created a general version (For a copy, please request via email at this stage).



Expectation Maximization (Multinomial algorithm example)

E Step (1)

Suppose we have true abundances

Transcript 1:500 (0.5)

Transcript 2: 200 (0.2)

Transcript 3: 300 (0.3)

But that we can only observe whether reads are in the following:

(T1,T3): 300+250 = 550

(T1,T2): 200+200 = 400

(T3): 50 = 50

It is typical to start with uniform probabilities for transcripts

$$\gamma_i^{(0)} = \frac{1}{N_r} \forall \ i$$

$$\gamma^{(0)} = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ 1 & 0 & 1 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 550 \\ 400 \\ 50 \end{bmatrix} = n$$

$$E(x|n, \gamma^{(0)}) = \begin{bmatrix} \frac{1}{3} + \frac{1}{3} \\ \frac{1}{3} \end{bmatrix}$$

$$\frac{\left(\frac{1}{3}\right)}{\frac{1}{3} + \frac{1}{3}}$$

$$\frac{\left|\frac{\overline{3}}{1}, \frac{1}{3}(550) + \frac{\overline{3}}{1}(400)\right|}{\frac{1}{3} + \frac{1}{3}}(400)$$

$$\frac{\left(\frac{1}{3}\right)}{\frac{1}{3} + \frac{1}{3}}(400)$$

$$\frac{\left(\frac{1}{3}\right)}{\frac{1}{3} + \frac{1}{3}}(550) + (1)(50)$$

$$= \begin{bmatrix} 475 \\ 200 \\ 325 \end{bmatrix}$$

$$\frac{\left(\frac{1}{3}\right)}{\frac{1}{3} + \frac{1}{3}}(550) + (1)(50)$$

$$\boldsymbol{\gamma}^{(1)} = \begin{bmatrix} \frac{475}{1000} & \frac{20}{100} & \frac{325}{1000} \\ 1 & 0 & 1 \\ 1 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 550 \\ 400 \\ 50 \end{bmatrix} = \boldsymbol{n}$$

$$\gamma^{(1)} = \begin{bmatrix} 0.475 \\ 0.2 \\ 0.325 \end{bmatrix}$$

M Step (1)

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Expectation Maximization (Multinomial algorithm example)

But that we can only observe whether reads are in the following:

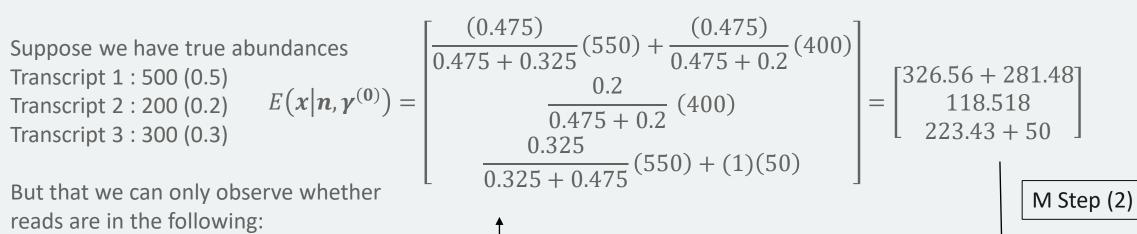
(T1,T3): 300+250 = 550

(T1,T2): 200+200 = 400

(T3): 50 = 50

It is typical to start with uniform probabilities for transcripts

$$\gamma_i^{(0)} = \frac{1}{N_r} \, \forall \, i$$



start with uniform or transcripts
$$\gamma_i^{(0)} = \frac{1}{N_r} \,\forall \, i$$

$$\gamma_i^{(0)} = \frac{1}{N_r} \,\forall \, i$$

E Step (2)

$$\gamma^{(2)} = \begin{bmatrix} 0.607 \\ 0.12 \\ 0.273 \end{bmatrix}$$

Converged?

$$|\gamma^{(2)} - \gamma^{(1)}| = \begin{vmatrix} 0.607 \\ 0.12 \\ 0.273 \end{vmatrix} - \begin{vmatrix} 0.475 \\ 0.2 \\ 0.325 \end{vmatrix} \le \varepsilon_R$$

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Questions about Expectation Maximization?



Break (10 Minutes)



Part 3: Genetic Transcript Abundance Quantification Software



Software for Genetic Abundance Quantification Salmon & Kallisto

- In order to quantify the true abundances of transcripts within a given genomic RNA-Seq sample, we use the Expectation Maximization algorithm following pseudo or quasi read alignment.
- Two packages which implement this approach are Salmon and Kallisto
 - **Salmon** was developed by Rob Patro, Geet Duggal, Michael Love, Rafael Irizarry, and Carl Kingsford and **published in 2017**. (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5600148/)
 - Kallisto was developed by Nicolas L. Bray, Harold Pimentel, Páll Melsted, and Lior Pachter and published in 2016. (https://www.nature.com/articles/nbt.3519/)

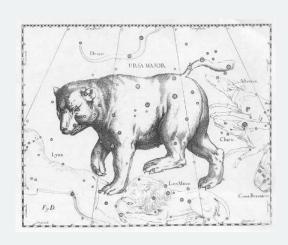


Image from Kallisto website.

• RSEM (RNA-Seq Expectation Maximization) was an earlier package which implemented expectation maximization on the incomplete/missing compatibility patterns:

Li B, Dewey CN. RSEM: accurate transcript quantification from RNA-Seq data with or without a reference genome. *BMC Bioinformatics*. 2011;12:323. Published 2011 Aug 4. doi:10.1186/1471-2105-12-323



Logo from SALMON website.



- Today, just follow along on the screen with me, tomorrow we will work through getting Kallisto and Salmon on your personal device, and working through some example problems with them together.
- In order to run Kallisto and Salmon, you first need to have a transcriptome in the FASTA format (from which the sequencing reads file of interest is taken)
 - Note if you do not have a transcriptome file, you might need to produce one by first parsing GTF/SNP/ or another Variant Call Format like file, and the reference sequence to which it corresponds.
 - For example, we created an RNA-Seq read simulator which will allow for us to produce a transcriptome file for GTF/SNP/FASTA (reference) files.
- In this short demonstration We will use an example transcriptome from a subset of genes on human chromosome 22.



• To access the help for either Salmon or Kallisto, you can use:

Running kallisto <CMD> without arguments prints usage

information for <CMD>

```
kallisto
                                                                                      Salmon -h
kallisto 0.46.0
                                                         salmon v1.8.0
Usage: kallisto <CMD> [arguments] ..
                                                                 salmon -h|--help or
                                                         Usage:
Where <CMD> can be one of:
                                                                  salmon -v|--version or
                                                                  salmon -c|--cite or
   index
                  Builds a kallisto index
                                                                  salmon [--no-version-check] <COMMAND> [-h
                  Runs the quantification algorithm
   quant
                                                          | options]
   bus
                  Generate BUS files for single-cell
data
                                                         Commands:
                  Runs the pseudoalignment step
   pseudo
                                                              index
                                                                          : create a salmon index
                 Merges several batch runs
   merge
                                                                          : quantify a sample
                                                               quant
   h5dump
                  Converts HDF5-formatted results to
                                                               alevin
                                                                          : single cell analysis
plaintext
                                                               swim
                                                                          : perform super-secret operation
   inspect
                  Inspects and gives information about
                                                               quantmerge: merge multiple quantifications
an index
                                                          into a single file
                  Prints version information
   version
                  Prints citation information
   cite
```



As we can see, Salmon and Kallisto have many options which are subdivided into sub-commands, to access the help for a subcommand you can use Kallisto <CMD>, or Salmon <CMD> -h Length of Kmer can be set The basic flow of using the tools is as follows: directly with options Transcriptome Kallisto index -i <index name> txome file.fa Salmon index -t <txome file> -i txome index Kallisto Index Salmon Index kallisto quant −i \ salmon quant -i sal idx -l A \ kal idx -o kal out \ -1 paired 1.fa \ Sequencing Reads Paired 1.fa -2 paired 2.fa \ paired 2.fa -o output quant **UTSouthwestern** Transcript Transcript **Medical Center** Quantification Quantification Results (Salmon) Results (Kallisto)

• Example Transcriptome file (Note Allele-Specific Names)

(base) micah@sw525709:~/projects/h2q/h2q/h2q/simulator\$ head c22.8.419.txome.fa -n 10>ENST00000521832

>ENST00000521832 alt

>ENST00000627251

>ENST00000627251 alt

>ENST0000040783

The transcriptome file can quickly become very large when dealing with many different transcripts of genes (and possible different allele-specific versions of the same transcript).

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Produce by internal Python Simulator (just inserts mutations):

Python hisat2 simulate reads -f ref.fa -g ref.gtf -s ref.snp -o ref.txome.fa

• From the transcriptome FASTA, we can use Kallisto & Salmon to produce their respective indexes (Colored De Brujin graph for Kallisto & K-mer table + Suffix Array for Salmon)

Produce Index from Transcriptome

EMBODIO 04 07 8 35

TADO CAMADO ECONOMICA CONTROLOGICA CONTROLOGICA CAMADO CONTROLOGICA CAMADA CONTROLOGICA CONTROLOGICA CONTROLOGICA CAMADO CONTROLOGICA CONTROL

```
build] loading fasta file ../c22.425.txome.fa
build] k-mer length: 31

Kallisto Index
```

```
build] k-mer length: 31

build] counting k-mers ... done.

build] building target de Bruijn graph ... done

build] creating equivalence classes ... done

build] target de Bruijn graph has 22 contigs and contains 2166 k-mers
```

```
proximateContigTotalLength: 1748
  rec>1 & succ>1)=0 | (succ>1 & isStart)=0 | (prec>1 & isEnd)=0 | (isStart & isEnd)=0
  ntig count: 23 element count: 2826 complex nodes: 0
 of ones in rank vector: 22
  022-06-27 11:49:10.477] [puff::index::jointLog] [info] Starting the Pufferfish indexing by reading the GFA binary file.
  022-06-27 11:49:10.478] [puff::index::jointLog] [info] Setting the index/BinaryGfa directory sal idx
  Loading contigs | Time = 8.6302 ms
                                                                        Salmon Index
  Loading contig boundaries | Time = 5.9665 ms
 umber of ones per inventory item: 512
 ventory entries filled: 1
 2022-06-27 11:49:10.506] [puff::index::jointLog] [info] Done wrapping the rank vector with a rank9sel structure.
  022-06-27 11:49:10.507] [puff::index::jointLog] [info] contig count for validation: 22
  022-06-27 11:49:10.510] [puff::index::jointLog] [info] Total # of Contigs : 22
  022-06-27 11:49:10.511] [puff::index::jointLog] [info] Total # of numerical Contigs : 22
  022-06-27 11:49:10.512] [puff::index::jointLog] [info] Total # of contig vec entries: 46
 2022-06-27 11:49:10.514] [puff::index::jointLog] [info] bits per offset entry 6
  022-06-27 11:49:10.518] [puff::index::jointLog] [info] Done constructing the contig vector. 23
  022-06-27 11:49:10.523] [puff::index::jointLog] [info] # segments = 22
  022-06-27 11:49:10.524] [puff::index::jointLog] [info] total length = 2,826
  022-06-27 11:49:10.525] [puff::index::jointLog] [info] Reading the reference files ...
  022-06-27 11:49:10.534] [puff::index::jointLog] [info] positional integer width = 12
  022-06-27 11:49:10.535] [puff::index::jointLog] [info] seqSize = 2,826
  022-06-27 11:49:10.536] [puff::index::jointLog] [info] rankSize = 2,826
  022-06-27 11:49:10.537] [puff::index::jointLog] [info] edgeVecSize = 0
  022-06-27 11:49:10.538] [puff::index::jointLog] [info] num keys = 2,166
 Building BooPHF] 100 % elapsed: 0 min 0 sec remaining: 0 min 0 sec
                 17472 bits (100.00 %) (array + ranks )
                      0 bits (0.00 %) (nb in final hash 0)
 022-06-27 11:49:10.676] [puff::index::jointLog] [info] mphf size = 0.00208282 MB
 2022-06-27 11:49:10.677] [puff::index::jointLog] [info] chunk size = 2,826
 2022-06-27 11:49:10.678] [puff::index::jointLog] [info] chunk 0 = [0, 2,796)
  022-06-27 11:49:10.679] [puff::index::jointLog] [info] finished populating pos vector
  022-06-27 11:49:10.679] [puff::index::jointLog] [info] writing index components
 2022-06-27 11:49:10.690] [puff::index::jointLog] [info] finished writing dense pufferfish index
[2022-06-27 11:49:10 702] [iLog] [info]
```



• Run the pseudo-alignment and quantification procedures using Kallisto and Salmon to produce the results (quantification of abundances).



Genetic Transcript Abundance Results

```
(base) micah@SW525709:~/projects/h2q/h2q/h2q/nanocourse$ cat c22.425.stat
ENSG00000185721 ENST00000331457 ref
                                         14996
ENSG00000185721 ENST00000331457 alt
                                         14996
                                                 snps
ENSG00000185721 ENST00000416465 ref
                                         6527
ENSG00000185721 ENST00000416465 alt
                                         6527
                                                 snps
                                         7757
ENSG00000185721 ENST00000433341 ref
                                                            True Simulation
ENSG00000185721 ENST00000433341 alt
                                         7757
                                                 snps
                                         5709
ENSG00000185721 ENST00000486584 ref
                                                            Positions
                                         5709
ENSG00000185721 ENST00000486584 alt
                                                 snps
                                         5118
ENSG00000185721 ENST00000469673 alt
                                         5117
                                                 snps
ENSG00000185721 ENST00000548143 ref
                                         9894
ENSG00000185721 ENST00000548143 alt
                                         9893
                                                 snps
```

```
(base) micah@SW525709:~/projects/h2q/h2q/h2q/nanocourse/salmon$ cd sal count/
(base) micah@SW525709:~/projects/h2q/h2q/h2q/nanocourse/salmon/sal count$ ls
aux info cmd info.json libParams lib format counts.json logs quant.sf
(base) micah@SW525709:~/projects/h2q/h2q/h2q/nanocourse/salmon/sal count$ cat quant.sf
       Length EffectiveLength TPM
                                        NumReads
ENST00000331457 1746
                        1495.297
                                       39821.114702
                                                        30031.986
ENST00000416465 612
                       361.297 71683.353315
                                               13062.473
                                               15405.660
ENST00000433341 808
                       557.297 54808.844438
                       67.297 336398.521190
                                               11418.000 Salmon Transcript Results
ENST00000486584 318
ENST00000469673 677
                        426.297 47881.328053
                                               10294.880
ENST00000548143 338
                               449406.838302
                                               19787.000
```

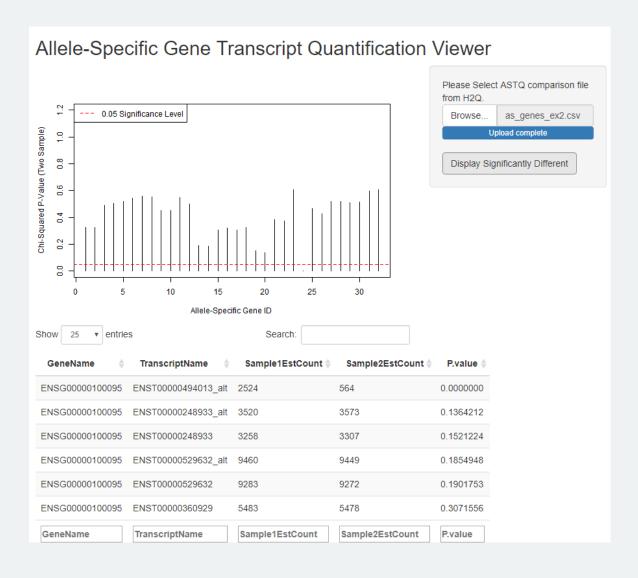
```
(base) micah@SW525709:~/projects/h2q/h2q/h2q/nanocourse/kallisto$ cd kal out/
(base) micah@SW525709:~/projects/h2q/h2q/h2q/nanocourse/kallisto/kal out$ ls
abundance.h5 abundance.tsv run info.json
(base) micah@SW525709:~/projects/h2q/h2q/h2q/nanocourse/kallisto/kal out$ cat abundance.
cat: abundance.: No such file or directory
(base) micah@SW525709:~/projects/h2q/h2q/h2q/nanocourse/kallisto/kal out$ cat abundance.tsv
               length eff length
target id
                                        est counts
                                                        tpm
ENST00000331457 1746
                        1497
                                30079.9 40686.8
ENST00000416465 612
                       363
                                11467.7 63968.9
                       559
ENST00000433341 808
                                16977.1 61496.8
                                                         Kallisto Transcript Results
                       69
ENST00000486584 318
                                11418
                                        335074
                       428
ENST00000469673 677
                                10270.3 48589.3
ENST00000548143 338
                        89
                                19787
                                        450184
```

Reads were simulated from allele-specific (randomly mutated) versions of 6 transcripts of gene ENSG00000185721

Since a non-allele specific transcriptome was used, Salmon and Kallisto cannot provide more specific quantification of these results than at the transcript level



Genetic Transcript (Allele-Specific Abundance Results with H2Q ~ Teaser)



- Procedures of HISAT2, we are able to produce exact alignments about as quickly as Kallisto and Salmon produce Pseudoalignments.
- This also allows us to identify allelic markers more easily (without rewriting the allelic variants into a transcriptome ahead of time).



Questions about Kallisto, Salmon and H2Q?



Day 1 Session 2 Summary

- 1. Pseudo-alignment/Quasi-mapping
- 2. Expectation Maximization in Coarsened Multinomial Data
- 3. Salmon, Kallisto, and H2Q (Introduction)

Day 2 Session 4 Topics

- 1. Additional information about Salmon and Kallisto
- 2. Statistical Procedures for Comparing Quantification Results
- 3. Practice Problem and Environment Set-up



Back-up (Bonus Material) – Day 1



Mathematical Background & Theory Proof of Jensen's Inequality

&

Derivation of Expectation Maximization (Chalk-Talk)



Expectation Maximization for Coarsened Multinomial Data Software Example

