# MACHINE LEARNING IN SYSTEMS BIOLOGY: Estimating the Size of the <br> Transcriptome 

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# Estimating the size of the transcriptome 

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High-throughput sequencing technologies ○○ 0
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How many species?


Solexa and Solid sequencing offer $10^{6}-10^{8}$ reads of length 20-60 nt at a price comparable to a micro-array.

- CAGE = cap analysis gene expression. 5' end of mRNAs. Pinpoints transcription start sites (TSSs). High throughput.
- EST = expressed sequence tag. Relatively low throughput. Used for gene identification.
- SAGE = Serial analysis of gene expression. Medium throughput and longer reads.
- ChIP/DNA/RNA seq or whole transcriptome shotgun sequencing. High throughput and longer reads.

- ChIP
- Chromatin ImmunoPrecipitation
- identifies protein-DNA interactions



Cerebellum library - frequency of frequency plot.

Setting up the problem

- Library of $n$ tags (reads)
- A sequence of genomic coordinates $\left(c_{1}, c_{2}, \ldots, c_{n}\right)$.
- Contains $k$ unique TSSs with counts $\mathbf{n}=\left(n_{1}, \ldots, n_{k}\right)$, $n=\sum_{j=1}^{k} n_{j}$.
- Label the tags in order of their arrival such that

$$
c_{i} \in\{1, \ldots, k\} .
$$

- The $n+1$ th tag may either be one of the $k$ previously seen TSSs or a new one:

$$
c_{n+1} \in\{1, \ldots, k, k+1\} .
$$

- Applied to this problem by Lijoi, Mena, Prünster, et. al.
- Observing new species given counts $\mathbf{n}=n_{1}, \ldots, n_{k}$ in $k$ bins:

$$
p\left(c_{n+1}=k+1 \mid \mathbf{n}, \sigma, \theta\right)=\frac{\theta+k \sigma}{n+\theta} \text { with } \sum_{i=1}^{k} n_{i}=n
$$

- Re-observing $j$ :

$$
P\left(c_{n+1}=j \mid \mathbf{n}, \sigma, \theta\right)=\frac{n_{j}-\sigma}{n+\theta}
$$

- Exchangeability - invariant to re-ordering

$$
\begin{array}{ll}
E, E, M, T, T: & p_{1}=\frac{\theta}{\theta} \frac{1-\sigma}{1+\theta} \frac{\theta+\sigma}{2+\theta} \frac{\theta+2 \sigma}{3+\theta} \frac{1-\sigma}{4+\theta} \\
M, E, T, T, E: & p_{2}=\frac{\theta}{\theta} \frac{\theta+\sigma}{1+\theta} \frac{\theta+2 \sigma}{2+\theta} \frac{1-\sigma}{3+\theta} \frac{1-\sigma}{4+\theta}=\ldots=p 1
\end{array}
$$

- Likelihood function, e.g. $E, E, M, T, T$

$$
\begin{aligned}
p(\mathbf{n} \mid \sigma, \theta) & =\frac{\theta}{\theta} \frac{1-\sigma}{1+\theta} \frac{\theta+\sigma}{2+\theta} \frac{\theta+2 \sigma}{3+\theta} \frac{1-\sigma}{4+\theta} \\
& =\frac{1}{\prod_{i=1}^{n-1}(i+\theta)} \prod_{j=1}^{k-1}(\theta+j \sigma) \prod_{i^{\prime}=1}^{k} \prod_{j^{\prime}=1}^{n_{i^{\prime}}-1}\left(j^{\prime}-\sigma\right)
\end{aligned}
$$

- Maximum likelihood (ML) inference or Gibbs sampling
- Predictions - simulate new sequence $c_{n+1}, c_{n+2}, \ldots, c_{n+n^{\prime}}$ using the sampling formula iteratively:

$$
p\left(c_{n+1}, \ldots, c_{n+n^{\prime}} \mid \mathbf{n}, \sigma_{\mathrm{ML}}, \theta_{\mathrm{ML}}\right)
$$

## Results




Cross-validated predictions from half to full size

- Model assigns a probability to each of the observed species, $j=1, \ldots, k$ :

$$
\frac{n_{j}-\sigma}{n+\theta}
$$

- What is the probability to see something we have already seen?
- Coverage (weight species by their observation probabilities):

$$
\text { Coverage }=\sum_{j=1}^{k} \frac{n_{j}-\sigma}{n+\theta}=1-\frac{\theta+k \sigma}{n+\theta} .
$$

- Empirical predictions from 95\%+ (genes) down to 60\% (genomic positions).
- Experimental technologies develop fast, lot to learn!
- Species sampling models accurate but not completely accurate for real data.
- Link to code and data:
http://people.binf.ku. dk/albin/supplementary_ data/tss_saturation/


