

# Past, present, and future of high-throughput genomics

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### outline



#### source: scitrends.com

### outline



#### source: scitrends.com

### outline





#### past / present

#### present / future

#### source: scitrends.com









#### genes



DNA subdivided into chromosomes

chromosomes further divided into regions called **genes** 

~20-25,000 genes in humans (exact number still unknown!)

### gene-expression (vastly simplified)



### gene-expression (vastly simplified)



### gene-expression (vastly simplified)



### past







### present













interested in exploring the noise introduced at each stage of sample-prep on reported results



raw Ct values





 $\Delta Ct$  values



shameless plug #1: (for further reading)

Kitchen et al. Methods (2010) vol. 50 (4)

### present











gene activity proportional to number of target molecules captured by bead





aim to generate profiles of genes that can **differentiate between disease states** 

single samples used often due to low availability of primary material and/or limited budget



Sørlie et al. 2003 PNAS

we're interested in **reproducibility** of microarray experiments

microarray quality control consortium (MAQC) engaged in 3stage project to assess arrays and RNA-seq

stage I [Nat Biotechnol (2006) vol. 24 (9)] looked at **crossplatform** and **inter-laboratory** consistency using dilution series of two reference RNA samples

we took a slightly different approach with a specific goal:

profile intra-experiment technical variation

- ✓ same laboratory
- $\checkmark$  same technology
- $\checkmark$  same type of RNA

	run I	r	un 2				r	un 3			run 4				run 5		
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Array QC:	Identification of batch variation:	Quantification of UHRR batch variation:	Comparison of UHRR & tumour variation:
Detection consistency and coefficient of variation analyses of UHRR replicates	Pairwise Pearson correlations of UHRR replicates	Impact of several normalisation methods assessed by ANOVA	Histograms showing differences in UHRR & tumour duplicates
UHRR included in batch corrections	Additional analysis of tumour duplicates	Duplicate tumour samples treated as duplicate experiments	Comparison of UHRR & tumour correlations:





- **B** standard normalisation
- C mean-centred
- D mean-centred & variance-adjusted







#### BMC Welcome University of Edinburgh (Subscriptions) (Log on / register) 3.93 Genomics Feedback | Support | My detail ome | journals A-Z | subject ar Research article **BMC Genomics** Volume 11 Correcting for intra-experiment variation in Illumina BeadChip data is Viewing options: necessary to generate robust gene-expression profiles Abstract PDF (6.1MB) Robert R Kitchen 😹, Vicky S Sabine 😹, Andrew H Sims 😹, E JANE Macaskill 😹, Lorna Renshaw 😹, Jeremy S Thomas 😹, Jano I van Hemert 24, J MICHAEL Dixon 24 and John M S Bartlett Associated material: Readers' comments [3] BMC Genomics 2010, 11:134 doi:10.1186/1471-2164-11-134 **Related literature:** Published: 24 February 2010 Other articles by authors ieon Google Scholar ieon PubMed Abstract (provisional) · Related articles/pages on Google on Google Scholar Background Tools: Microarray technology is a popular means of producing whole genome transcriptional profiles, however high cost and scarcity of mRNA Download citation(s) has led many studies to be conducted based on the analysis of single samples. We exploit the design of the Illumina platform, specifically · Email to a friend multiple arrays on each chip, to evaluate intra-experiment technical variation using repeated hybridisations of universal human reference Order reprints RNA (UHRR) and duplicate hybridisations of primary breast tumour samples from a clinical study. Post a comment Post to: Citeulike Results Connotea A clear batch-specific bias was detected in the measured expressions of both the UHRR and clinical samples. This bias was found to Pel.icio.us persist following standard microarray normalisation techniques. However, when mean-centering or empirical Bayes batch-correction Facebook methods (ComBat) were applied to the data, inter-batch variation in the UHRR and clinical samples were greatly reduced. Correlation Mendeley Twitter between replicate UHRR samples improved by two orders of magnitude following batch-correction using ComBat (ranging from 0.9833-0.9991 to 0.9997-0.9999) and increased the consistency of the gene-lists from the duplicate clinical samples, from 11.6% in quantile normalised data to 66.4% in batch-corrected data. The use of UHRR as an inter-batch calibrator provided a small additional benefit when used in conjunction with ComBat, further increasing the agreement between the two gene-lists, up to 74.1%. Conclusion

In the interests of marticalities and cost, these results success that single samples can generate reliable data, but only after marticalities estion for technical bias in

### Kitchen et al. BMC Genomics (2010) vol. 11 (1)

current interest is in correlating observed experiment noise with specific **probe properties**:



eg: TGGGAAAGAACACAGAGGAATCCAGCCATTTCCACAGCGTCCAGCTCTGC

current interest is in correlating observed experiment noise with specific **probe properties**:

for example:

- probe position within target gene
- number of transcripts consecutively hit by the probe
- ➡ GC content
- ➡ CpG count
- rough total length of target gene







### present

















#### correlation

#### 99.6%

#### 99.5%

96.4%







#### first run



#### second run



#### second run - fresh samples

### label-free proteomics

similar, in principle, to RNA-seq:

#### RNAseq

- ✓ many short fragments
- ✓ assign fragments to parent RNA transcript
- ✓ incomplete reference

### LF-MS/MS proteomics

- ✓ many short fragments
- ✓ assign fragments to parent protein
- ✓ very incomplete reference

### label-free proteomics

LF-MS/MS proteomics experiments currently rely on curated protein reference databases for peptide assignment

such reliance limits its effectiveness as a discovery tool

from our data, a typical rate of peptide assignment ~30%

Bitton et al. (2010) used an *in-silico* translation of the entire human genome & identified 346 'putative' novel peptides

### future





### integrated RNAseq / proteomics

RNAseq data lends itself perfectly as a source of protein reference

perform *in-silico* translation of RNA known to be present in a given set of samples -- map peptides to this reference

RNA/protein **expression analysed simultaneously**, reduce false-positives etc.

### integrated RNAseq / proteomics

our own, very preliminary, very naïve analysis shows promise:



### integrated RNAseq / proteomics



compared to protein direction of change:

53% of array probes agree ( $\chi^2$  pVal=0.886) 71% of exon-level RNA-seq agree ( $\chi^2$  pVal=0.012) 100% of gene-level RNA-seq agree (only 5 of them...)

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