

Statistical Methods for High Dimensional Biology

STAT/BIOF/GSAT 540

Lecture I – course introduction
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January 4 2017

Today's topics

- What the course is about
- Course mechanics – details and up-to-date info will be at <https://stat540-ubc.github.io/>
(These lecture notes are just an overview)
- A primer on molecular biology
- Introduction to high-dimensional biology

Your instructors

- **Dr. Paul Pavlidis** – Professor of Psychiatry/Michael Smith Labs
 - paul@msl.ubc.ca
 - Bring administration questions to me
- **Dr. Amrit Singh** – Dept. Pathology & Lab Medicine /Centre for Heart and Lung Innovation @ St. Paul's
- **Dr. Rob Balshaw** – Dept. of Statistics and BC CDC
- **TAs: Farnush Farhadi** (farnush.farhadi@gmail.com),
Santina Lin (Part-time; hello@santina.me)

Course audience

- Researchers who want to know how to analyze large data sets from biological studies
- Genomics-oriented, but focus on broadly applicable statistical approaches
- Statistics students might find the math parts easy
- Biology students might find the biology easy
- We are counting on you to help make it work: help your peers!

Prerequisites

Officially, none. But:

- **Statistics** – You should have already taken university level “Statistics 101”. You’ll get a refresher, but you should be prepared to get comfortable thinking about things like “probabilities” and “specificity”.
- **Biology – No requirements**, but you are expected to learn things like the difference between a DNA and RNA and a gene and a genome. We assume you are here because you are interested in biology and will pick it up.
- **No R** experience required but you must be prepared to do a lot of self-guided learning.
- You’ll use your own computer to run R. If you can’t install R on your computer, ask us for options.

What you can expect to learn

- Conceptual and practical knowledge you need to handle large biological data sets
 - Generally applicable approaches and principles
 - Specifics about some data types (esp. expression profiling)
 - Limited details on “low-level” processing
- Critically evaluate analyses in the literature and avoid pitfalls in your own research.
- Implement analyses using the R/Bioconductor statistical computing environment
 - Limited coverage of underlying math & theory
- Use Github for project management and reproducibility of research

Topics covered in the course

Probability foundations

Exploratory data analysis

Data QC and preprocessing

Basic statistical inference (“one gene at a time”)

Large-scale inference (“genome-wide”) – multiple testing

Count-based data (e.g. RNA-seq) analysis

DNA methylation analysis

Principal Component Analysis

Clustering

Classification

Resampling and bootstrap

Model selection and regularization

Gene sets and gene networks

<https://stat540-ubc.github.io/subpages/syllabus.html>

Course mechanics

Course web site (Github)

<http://stat540-ubc.github.io>

- Lecture notes
- Lab notes
- Assignments

Much interaction via the site (discussions, submission)

Don't email the instructors a question that would benefit the class – open a Github issue!

TAs will help you get you set up with Github (more on this later)

Lectures

- Two per week, will start promptly at 9:30
- Lectures shared among three instructors (and guest lecturers)
- Generally the notes will be provided on web before class, otherwise immediately following.

Seminars (“Labs”)

- Wednesdays in room ESB 1042
- 11AM-1PM – please plan on coming for one hour. For first session (TODAY):
 - 11-12:30 R and github setup help
 - 12:30-1:00 Mol. Bio. Primer

What’s in the labs?

- First half of course: Self-guided exercises using R
 - Using your own computer (other options possible)
 - Exercise material will be made available ahead of time
- Towards end of course, devoted to working on group projects.

Readings

- No textbook, but we can give suggestions
- Lectures often come with suggested background papers (reviews or primary literature)
- Helpful to access journals online (e.g. via the UBC VPN)
 - <https://it.ubc.ca/services/email-voice-internet/myvpn>

Evaluation

- **Homework**
 - Assignment worth 30 points – in two parts (plus one 'setup' assignment worth 5 points)
- **Group project**
 - Planning + project + poster session + report = 60 points
- **Short writing assignment**
 - 5 points

(Note changes from last year!)

Homework assignment

- Involve detailed analysis of real data
- Deliverables include a short report and R code
- Will have two weeks from assignment to due date
- Lateness penalties

Short writing assignment

- Revised for this term
- Meant to develop your skills relating course material to the literature
- Select, read, summarize and critique a recent paper from the 'omics literature
- Details to follow

Group projects

- Starts **today** – start thinking about it
- A few minutes for group project pitches later this month during lecture time, also proposed via github
- Form groups by Fri Jan 25 (4-5 people) and provide an initial rough project proposal
- You'll get feedback from instructors
- Proposals finalized by Feb 15
- Work on projects over rest of term
- Final session of the course is the poster session

Dates may change – refer to course site

Group projects: where do they come from?

- Nearly all projects have been based on a data set provided by a student (i.e., collected in their lab).
- Occasionally using published data.
- If you need help thinking up an idea for a project let us know. But this has never been needed before (beyond refinement). If you are unsure of where you are going to get a project from, wait until you hear the project pitches.

Examples of past group projects

- Genomic copy number alterations for prognosis of prostate cancer
- Learning about proteins from other proteins: Protein Database Prediction
- Conditional epistasis profiling in yeast
- Epigenetic biomarkers for cancer diagnosis
- Comparative metagenomics : metabolic potential
- Epigenome and transcriptome in rice strains
- Analysis of HPV E2 protein on host gene expression
- Effects of mutations in histone modifying enzymes on gene expression profiles
- Methodological considerations in analysis of Illumina Infinium methylation data
- Gene expression in invasive ragweeds
- Modeling time-course expression of SET domain-containing genes in mouse embryos
- Gene expression in blood of humans with asthma challenged with allergen

2011 and 2012 project titles, paraphrased

Your first assignment

- Due in two weeks (Jan 18) – 5 points
- See https://github.com/STAT540-UBC/STAT540-UBC.github.io/blob/master/homework/practice_assignment/practice_assignment.md
- You will get to:
 - Set up your github environment
 - Get R installed and cover some basics
 - Make your first github commits.

First step ASAP: complete survey at
<https://goo.gl/forms/P8pRUppM2XLIJNQL2>

Setting up for STAT540, 2017

Hi, let me help you set up a GitHub repo in the STAT540 GitHub organization !

* Required

Molecular biology in 5 slides

Ignoring many exceptions and complications!

- **DNA:** linear arrangement of nucleotides ('bases'), contains information to construct the organism; provides mechanism of heritability
 - Every time a cell divides, the DNA is copied (**replicated**)
- **Gene:** a stretch of DNA that is transcribed into a functional RNA
 - Simplest genomes contain ~1000 genes (e.g.: E. coli has ~4000, yeast has ~6000)
 - Most multicellular organisms have ~15-25k genes (e.g. worms, flies, vertebrates)
- **Genome:** the full complement of DNA in one cell
 - The sequence of the DNA is the **genotype**; can refer to a specific place ("locus") or overall.
 - The properties of the organism produced is the **phenotype**
- **RNA:** Immediate read-out of a gene, also made of nucleotides ("transcript")
 - Complication: Splicing. Primary transcript is of exon and intron regions, latter are removed; "**exome**" is the set of all exons. A single processed transcript is a messenger or mRNA.
- **Protein:** Major working parts of cells, encoded by genes (via RNA) and made ("translated") by the ribosome (a big molecular machine)
 - Proteins are strings of amino acids ("polypeptides"); 3 nucleotides code one AA
- DNA, RNA and protein (plus many other types of molecules used by cells) are produced using chemicals (from air and food) and energy from sunlight (directly or indirectly via food) = "**metabolism**", a process which involves the function of (at least) hundreds of genes.

The human genome

(a typical mammalian genome)

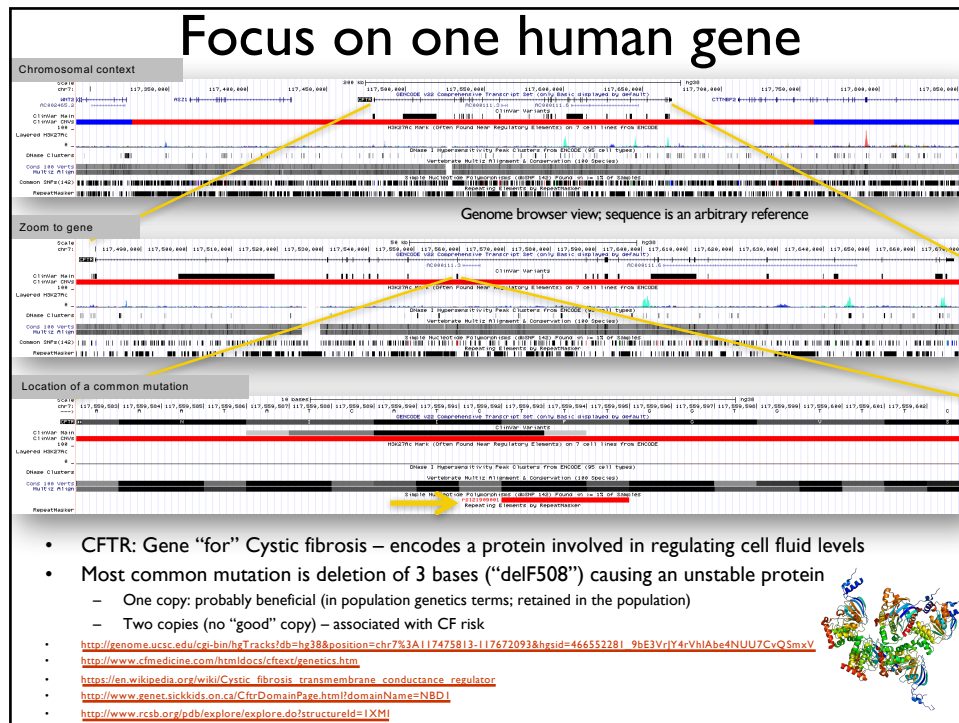
- ~6 billion bases of DNA over 23 pairs of chromosomes (3 billion bases in "haploid")
- Of the total 46 chromosomes, you got 23 from mom and 23 from dad
- ~10-15% of the human genome is functional – the rest is "junk"
 - 10-15% includes exons of genes and regulatory elements
 - Balance includes bulk of introns and intergenic regions
- About 20,000 protein-coding genes +some RNA-only genes

Molecular regulation

- Not all genes are active in any given cell
 - Many organisms are made of different types of cells – the differences are established by changing which genes are active
 - All organisms regulate which genes are active depending on the environment
- Regulation happens at multiple levels (transcription, translation, post-translation)
- System of signals, receptors, switches = complex “wiring” of genes with each other and with the environment – goal of “systems biology” is to understand this in full detail.

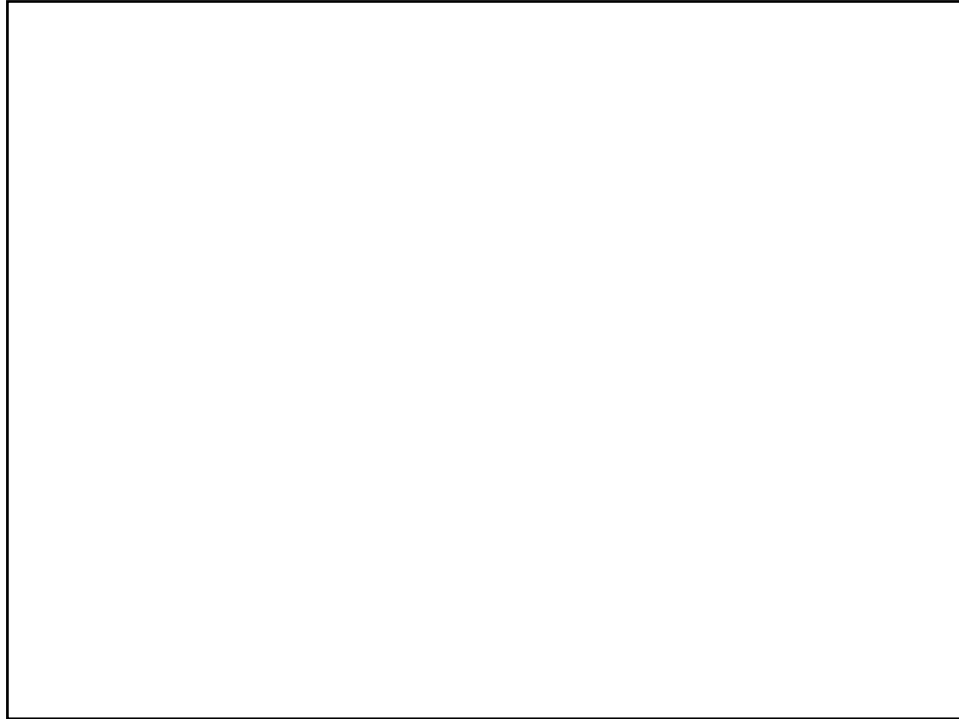
Genetic variation

- Differences in DNA sequence between two individuals of the same species (different genotypes) – humans: millions of differences
- Most are inherited from mom and dad, but also acquired during your life.
 - Depending on when acquired, will affect all or part of your body.
- Most variation has no effect on phenotype (“neutral” or nearly)
 - Occurs in a junk region, is silent (degeneracy of amino acid code), or affects an “unimportant” gene
- Some variation is “deleterious”
 - Slightly deleterious: increases your risk of disease; can be hard to detect
 - Highly deleterious: mutations “cause” disease; e.g. Cystic fibrosis
- Even more rarely variation can be “beneficial”
- In population genetics “deleterious” and “beneficial” are defined by effects on **reproductive success** (how many descendants you have), but we can also talk about it in terms of the effect on the gene’s biochemical function.



Key points...

- Thousands of “moving parts” (e.g. genes)
- Hugely complex interactions and regulation – poorly understood
- Many genes have poorly understood function
- Genetic variation and environment interact in complex ways
- Many diseases have a genetic component still to be understood.
 - Same applies to non-humans (plant disease resistance, etc.)
- Reductionist paradigm: conceptually works backwards from the phenotype to the genotype, attempting to resolve the steps in between



High-dimensional biology

1. What, why and how
2. Overview methods are used to analyze it

Collecting data the low-dimensional way

- Pick one variable (e.g. “activity of a protein”) and study it under various conditions.
- Repeat this for another variable
- Usually “hypothesis-driven”
 - CFTR is a classic example of this in operation for a genetic disease
- Powerful, but knowledge accumulates slowly and synthesis is difficult

The move to “systems biology”

- Limitations of the “one thing at a time approach” – how do the parts work together?
- Technology enabling increasingly detailed analyses – measure many things in parallel
- Drawbacks/cautions
 - Still far underpowered to reverse engineer everything
 - Fishing expeditions
 - Looking under the technological streetlamp

Defining “high dimensional”

- Large number of features measured in each sample/subject/individual (“high content”)
 - Genes, proteins, DNA sites, brain regions, etc.
- Not *usually* talking about huge numbers of samples (e.g. individuals studied) –
 - often 10s, but can be 1000s (some genetics studies)

Many things to assay...

In this course, we are largely concerned with quantitative measurements of genomic features specifically:

- Gene transcript levels (RNA)
- DNA methylation (Lecture 15 and Seminar 8)

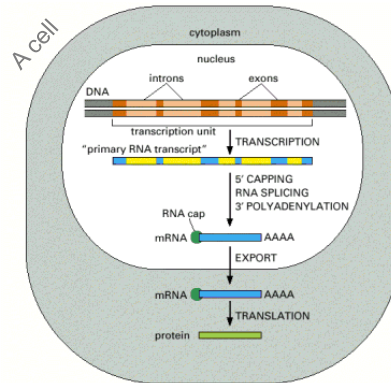
Contrast with analysis of DNA sequence

- Closest analogue in course scope is Genome Wide Association Analysis (GWAS)
- Characterization of rare variants in individual genomes is another major area of study (Lecture 23)

However, many of the statistical approaches and issues are relevant to many data types

- Protein levels (quantitative proteomics)
- Metabolomes (quantitative small molecule analysis)
- Microbiomes (quantitative analysis of microbe species distributions)
- Functional brain imaging (units of analysis are brain regions)

Gene expression



(Diagram shows just one gene)

At RNA level, regulatory points include:

- Rate of transcription
- Rate of modification (splicing etc.) and export to the cytoplasm
- Rate of degradation

Alberts, Molecular Biology of the Cell

Why study gene expression?

- The **“readout” of genetic variation** is partly in gene expression – it can help us understand the link between genetics and phenotypes
- **Genes expression is regulated** and changes in response to environment, disease, age, etc.
- Genes are expressed at an appropriate time and place: we can learn (or guess) about gene function by comparing expression patterns (**guilt-by-association**)
- The pattern of gene expression can be used as a **‘fingerprint’ of the state the sample** was in at the time of measurement – a biomarker
- Examining the details about which genes are relevant to the fingerprint (“differentially expressed”) give **insight into the process/disease/condition** of interest.

High-dimensional technologies

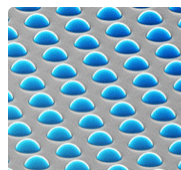
In this course 99% of the experiments we discuss involve one of two basic technologies:

Microarrays

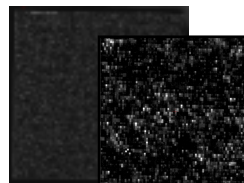
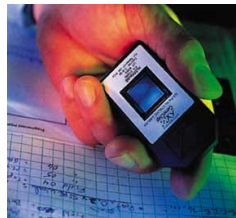
Massively parallel nucleotide sequencing

Microarrays

Illumina Beadarray



Affymetrix Genechip



- Substrate glass slide contains specific short DNA probes for genes of interest.
- Each spot is one probe sequence; possibly multiple spots for a given gene.
- **Hybridize** a labeled mixture of RNA from sample.
- Readout: expression level for many genes for one sample
- Variants of same idea can be used for DNA site-specific sequence and methylation analysis

Sequencing-based assays

- Instead of using hybridization to a designed probe, determine many (millions) of short randomly-selected sequences from the sample.
- RNA: quantify how many times you see a sequence (~mRNA molecule)
- Same technology can also be used for DNA Methylation and genome sequencing.



Up to eight samples can be loaded onto the flow cell for simultaneous analysis on the Illumina Genome Analyzer.

Illumina

A typical genomics study

Motivation:

- Tumor type A is deadly while type B is more treatable
- Telling A from B is difficult using “conventional” means
 - Cells look the same, etc. – we only find out by seeing what happens to the patients.

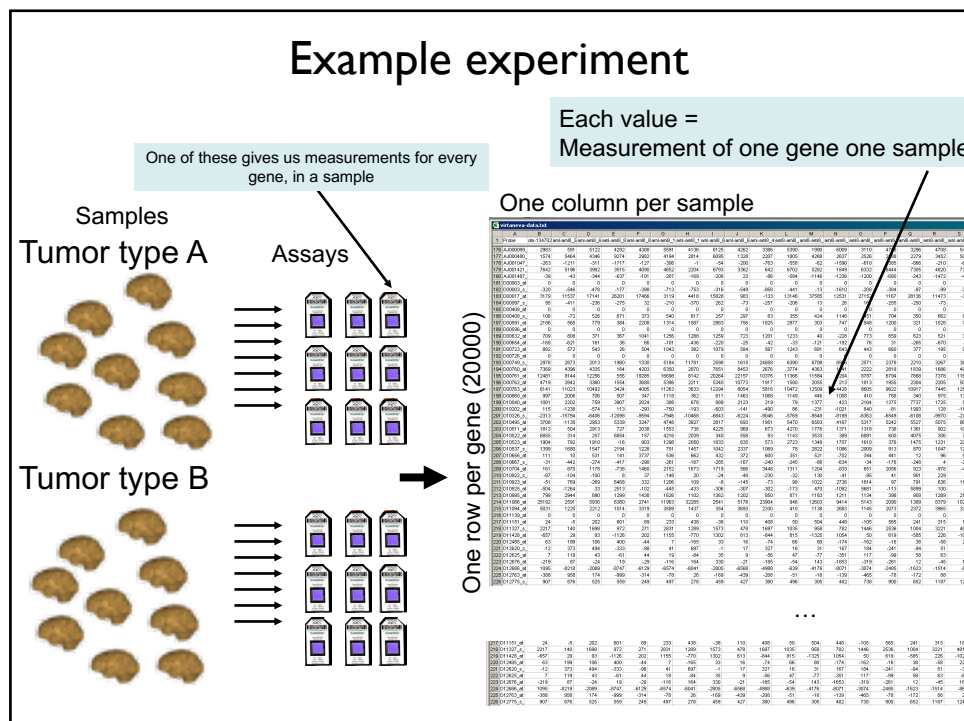
Questions:

- Can we characterize the differences better?
- Can we find new targets for drugs or for diagnosis?
 - Drug targets are usually proteins, encoded by genes
- Are there other subtypes that can be described?

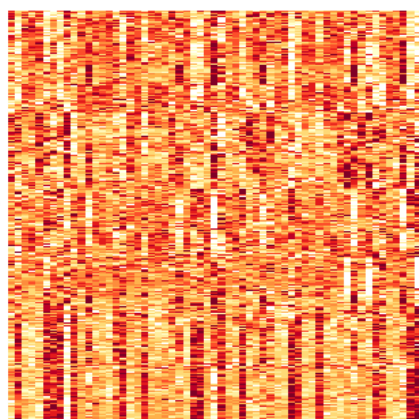
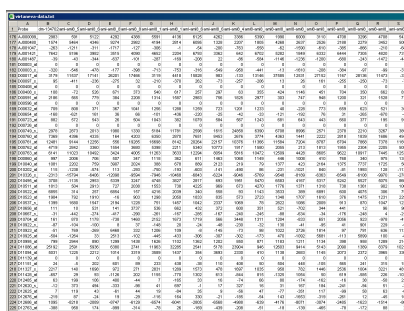
Looking for insight from genomics

- We are hypothesizing that there is *some* difference in genes between the two types, if only we could find it
- But we're not starting with a *specific* hypothesis. We're going to test thousands of hypotheses
- In this example, we're going to look at "gene expression levels" – a measure of "how active" is each gene.

This example is only partly realistic: these days, DNA sequencing would probably be done as well. Looking at RNA is still a useful adjunct to examining the DNA.

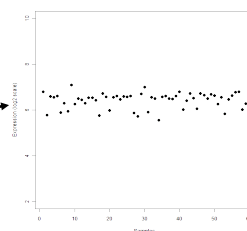
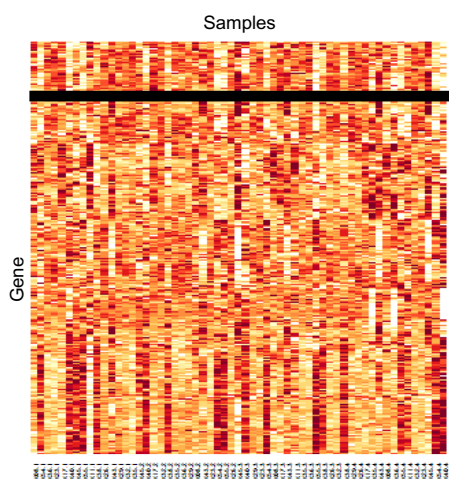


Alternative representation



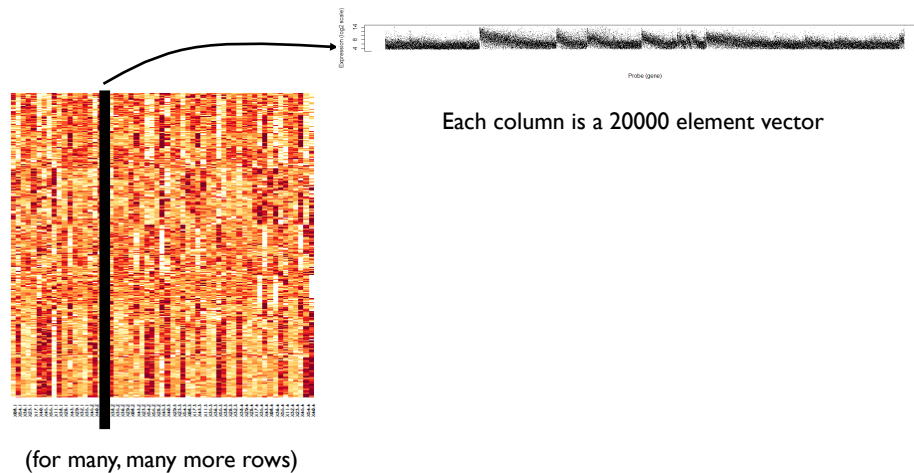
Lighter colours mean higher levels of gene expression ("activity")
Only show part of the data!

Profile for a gene



Profile for a gene. This is a 59-element vector

Profile for a sample

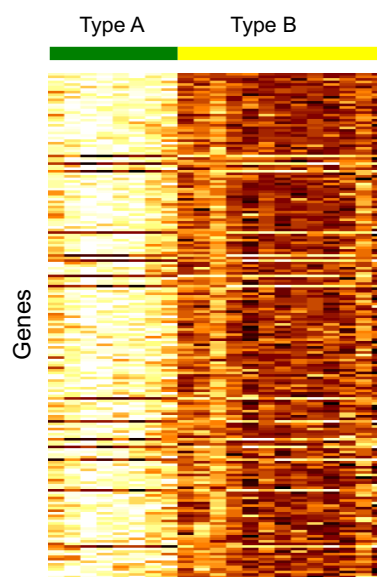


*This is a schematic. The graph and color map don't match

One type of analysis

- I've ranked the genes by how different they are between types A and B (t-statistic)
- Mostly "underexpressed" in Type B
- Only the first few genes are shown
- Though it can be a lot more complicated, most "high-dimensional" studies boil down to something like this, at least in part

What's the big deal?



Pitfalls and challenges

- Signals can be small relative to non-signal: data are noisy with finite sensitivity. **False negatives** are often a given, and **false positives** are a major danger.
- Need to address outliers, batch effects and other systematic **artifacts** (can dominate signal)
- Dealing with and exploiting biological and statistical dependencies – e.g. genes are not independent
- Getting just a list of “hits” isn’t enough – can we understand something more about the “system”
- Data sets (and questions) can be much more complex than my simple example; perhaps most interestingly when you have multiple data types for the same samples (e.g. DNA sequence, DNA methylation and RNA levels)

Analysis modes

- What is the general toolkit available for the analysis of data?
- How are these specialized for high-dimensional data?

Exploratory analysis

- The first thing you do with your data
- Graphs and other visualizations, often combined with data reduction
- Use to spot problems, formulate hypotheses
- Often rely on power of human brain
- Data reduction essential to make exploration tractable for large data sets, even then it can be a challenge
- Follow up with more formal analysis

Model fitting and hypothesis testing

- Formally test a specific question about the data
- Is what I see “statistically significant”?
- False positives are a major risk in large data sets
- Can exploit repeating structure of the data to improve ability to find true positives

Unsupervised learning

- “Learn” undiscovered groupings in the data
- Clustering -- how do my samples or features group together?
- Useful as an exploratory technique as well as “data mining” when backed with quantitative analyses
- Example: Finding previously unknown groups of subjects based on a gene profile

Supervised learning

- Can I predict an unmeasured feature of a sample from a measured one?
- Less common than unsupervised learning, most used in clinically-oriented settings – development of **biomarkers**
- Example: predicting tumour drug response based on gene profiles

Other methods

- Many analyses just give a list of genes
- “Downstream” analysis needed to make sense of it - “biological interpretation”
 - Overlay/combine/compare with other data
 - Transform one data set into another type of data at a different granularity
 - Genes → pathways
- Usually these end up returning to exploratory etc. modes

Enjoy the course!