Jon K. Lærdahl,
Structural Bioinformatics

Bioinformatics for Molecular Biology

Databases & Accessing data

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Today's Programme

- Biological databases
- Brief introduction
  - What is UNIX?
  - Why should you learn UNIX?
- Bioinformatics Core Facility
- Setting up your laptops

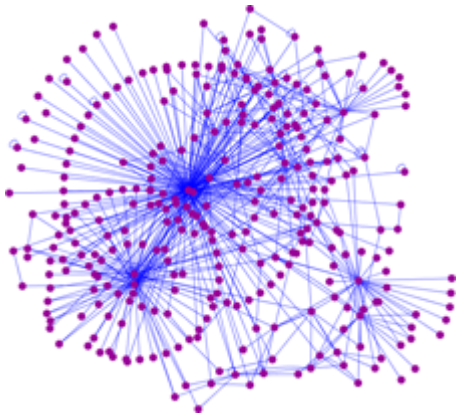
What about those of you that know Unix and Python very well?

- Very briefly on the Unix shell, file system and some commands
- UNIX basics exercise
- Tomorrow, continue on databases & working with biological sequences

Bioinformatics is the field of science in which biology, computer science, and information technology merge to form a single discipline. The ultimate goal of the field is to enable the discovery of new biological insights as well as to create a global perspective from which unifying principles in biology can be discerned.

NCBI – A Science Primer

Biology in the 21st century is being transformed from a purely lab-based science to an information science as well.



Wikipedia:

Bioinformatics is a branch of biological science which deals with the study of methods for storing, retrieving and analyzing biological data, such as nucleic acid (DNA/RNA) and protein sequence, structure, function, pathways and genetic interactions. It generates new knowledge that is useful in such fields as drug design and development of new software tools to create that knowledge. Bioinformatics also deals with algorithms, databases and information systems, web technologies, artificial intelligence and soft computing, information and computation theory, structural biology, software engineering, data mining, image processing, modeling and simulation, discrete mathematics, control and system theory, circuit theory, and statistics.

Bigger than biology?

NIH WORKING DEFINITION OF BIOINFORMATICS AND COMPUTATIONAL BIOLOGY

July 17, 2000

The following working definition of bioinformatics and computational biology were developed by the BISTIC Definition Committee and released on July 17, 2000. The committee was chaired by Dr. Michael Huerta of the National Institute of Mental Health and consisted of the following members:

Bioinformatics Definition Committee

BISTIC Members	**Expert Members**
Michael Huerta (Chair)	Gregory Downing
Florence Haseltine	Belinda Seto
Yuan Liu	

Preamble

Bioinformatics and computational biology are rooted in life sciences as well as computer and information sciences and technologies. Both of these interdisciplinary approaches draw from specific disciplines such as mathematics, physics, computer science and engineering, biology, and behavioral science. Bioinformatics and computational biology each maintain close interactions with life sciences to realize their full potential. Bioinformatics applies principles of information sciences and technologies to make the vast, diverse, and complex life sciences data more understandable and useful. Computational biology uses mathematical and computational approaches to address theoretical and experimental questions in biology. Although bioinformatics and computational biology are distinct, there is also significant overlap and activity at their interface.

Definition

The NIH Biomedical Information Science and Technology Initiative Consortium agreed on the following definitions of bioinformatics and computational biology recognizing that no definition could completely eliminate overlap with other activities or preclude variations in interpretation by different individuals and organizations.

Bioinformatics: Research, development, or application of computational tools and approaches for expanding the use of biological, medical, behavioral or health data, including those to acquire, store, organize, archive, analyze, or visualize such data.

Computational Biology: The development and application of data-analytical and theoretical methods, mathematical modeling and computational simulation techniques to the study of biological, behavioral, and social systems.

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Certainly not exactly clear distinction between bioinformatics and the rest of science

CLS (Computational Life Science)

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If you want to do state-of-the art research in biology or molecular medicine in 2014 you need bioinformatics/CLS/informatics competence!!

Some examples

Vol 467|2 September 2010|doi:10.1038/nature09322

nature

LETTERS

Genome-wide measurement of RNA secondary structure in yeast

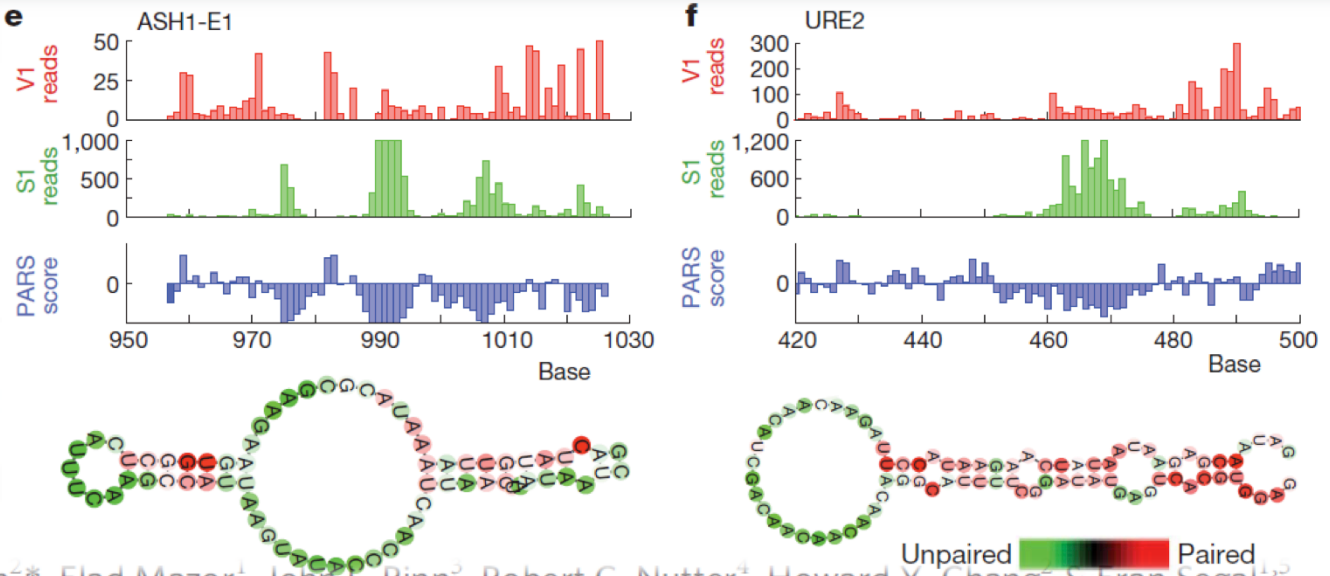
Michael Kertesz[1]*†, Yue Wan[2]*, Elad Mazor[1], John L. Rinn[3], Robert C. Nutter[4], Howard Y. Chang[2] & Eran Segal[1,5]

The structures of RNA molecules are often important for their function and regulation[1–6], yet there are no experimental techniques for genome-scale measurement of RNA structure. Here we describe a novel strategy termed parallel analysis of RNA structure (PARS), which is based on deep sequencing fragments of RNAs that were treated with structure-specific enzymes, thus providing simultaneous *in vitro* profiling of the secondary structure of thousands of RNA species at single nucleotide resolution. We apply PARS to profile the secondary structure of the messenger RNAs (mRNAs) of the budding yeast *Saccharomyces cerevisiae* and obtain structural profiles for over 3,000 distinct transcripts. Analysis of these profiles reveals several RNA structural properties of yeast transcripts, including the existence of more secondary structure over coding regions compared with untranslated regions, a three-nucleotide periodicity of secondary structure across coding regions and an anti-correlation between the efficiency with which an mRNA is translated and the structure over its translation start site. PARS is readily applicable to other organisms and to profiling RNA structure in diverse conditions, thus enabling studies of the dynamics of secondary structure at a genomic scale.

that typically have 5′ hydroxyl (Supplementary Fig. 3). Thus each observed cleavage site provides evidence that the cut nucleotide was in a double-stranded (for V1-treated samples) or single-stranded (for S1-treated samples) conformation. As a quantitative measure at nucleotide resolution representing the degree to which a nucleotide was in a double- or single-stranded conformation, we took the log ratio between the number of sequence reads obtained for each nucleotide in the V1 and S1 experiments. A higher (lower) log ratio, or PARS score, thus denotes a higher (lower) probability for a nucleotide to be in a double-stranded conformation.

We performed four independent V1 experiments and three independent S1 experiments, which were highly reproducible across replicates (correlation = 0.60–0.93, Supplementary Table 1), resulting in over 85 million sequence reads that map to the yeast genome, of which approximately 97% mapped to annotated transcripts (Supplementary Table 2). At an average nucleotide coverage above 1.0, we obtained structural information for over 3,000 yeast transcripts (Supplementary Table 3 and Supplementary Fig. 4a), covering in total over 4.2 million transcribed bases, which is approximately 100-fold more than all published RNA footprints to date.

Vol 467|2 September 2010|doi:10.103



Genome-wide structure in y

Michael Kertesz[1]*†, Yue Wan[2]*, Elad Mazor[1], John L. Rinn[3], Robert C. Nutter[4], Howard Y. Chang[2] & Eran Segal[1,5]

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Try to do this without (bio)informatics skills?

PROTOCOL

Defining transcribed regions using RNA-seq

Brian T Wilhelm[1,4], Samuel Marguerat[2,4], Ian Goodhead[3] & Jürg Bähler[2]

[1]Institute for Research in Immunology and Cancer (IRIC), Université de Montréal, Montréal, Québec, Canada. [2]Department of Genetics, Evolution & Environment and UCL Cancer Institute, University College London, London, UK. [3]Unit for Functional and Comparative Genomics, School of Biological Sciences, University of Liverpool, Liverpool, UK. [4]These authors contributed equally to this work. Correspondence should be addressed to J.B. (j.bahler@ucl.ac.uk).

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Next-generation sequencing technologies are revolutionizing genomics research. It is now possible to generate gigabase pairs of DNA sequence within a week without time-consuming cloning or massive infrastructure. This technology has recently been applied to the development of 'RNA-seq' techniques for sequencing cDNA from various organisms, with the goal of characterizing entire transcriptomes. These methods provide unprecedented resolution and depth of data, enabling simultaneous quantification of gene expression, discovery of novel transcripts and exons, and measurement of splicing efficiency. We present here a validated protocol for nonstrand-specific transcriptome sequencing via RNA-seq, describing the library preparation process and outlining the bioinformatic analysis procedure. While sample preparation and sequencing take a fairly short period of time (1–2 weeks), the downstream analysis is by far the most challenging and time-consuming aspect and can take weeks to months, depending on the experimental objectives.

Lab: 1 week for one trained engineer?
Bioinformatics: Months of work!
This is the real research work?

Nat. Protoc. **5**, 256 (2010)

Vol 463|21 January 2010|doi:10.1038/nature08696 nature

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ARTICLES

The sequence and *de novo* assembly of the giant pan

Travelled around in China and took blood samples from pandas

Ruiqiang Li[1,2]*, W… Jing Cai[3,6]*, Quanfei Huang[1], Qingle Cai[1,7], Bo Li[1], Yinqi Bai[1], Z… Fuwen Wei[9], Heng Li[10], Min Jian[1], Jianwen Li[1], Zhaolei Zhang[11], Rasm… …entao Yang[1], Zhaoling Xuan[1], Oliver A. Ryder[14], Frederick Chi-Ching Leung[15], Yan Zhou, Jianjun Cao, Xiao Sun[16], Yonggui Fu[17], Xiaodong Fang[1], Xiaosen Guo[1], Bo Wang[1], Rong Hou[8], Fujun Shen[8], Bo Mu[1], Peixiang Ni[1], Runmao Lin[1], Wubin Qian[1], Guodong Wang[3,6], Chang Yu[1], Wenhui Nie[6], Jinhuan Wang[6], Zhigang Wu[1], Huiqing Liang[1], Jiumeng Min[1,7], Qi Wu[9], Shifeng Cheng[1,7], Jue Ruan[1,3], Mingwe… …Wen[1], Binghang Liu[1], Xiaoli Ren[1], Huisong Zheng[1], Dong Dong[11], Kathl… …g[1], C… Yingrui Li[1], Cy… …Tommy T… Timing Gong[1], Hongde Liu[16], Dejin Zhang[16], Yuanyuan Ren[1], Guojie Zhang[1,3,6], Michael … Yang Zheng[1,3], Yongyong Shi[5], Zhiqiang Li[5], Feng Tian[1], Xiaoling Wang[1], Haiyin Wang[1], Siu-Ming Yiu[22], Shiping Liu[23], Hemin Zhang… Junyi Wang[1], Nan Qin[1], Li Li[1], Jingxiang Li[1], Maynard Olson[26], Xiuqing Zhang[1], Songgan…

Wet lab?

Using next-generation sequencing technology a… giant pa… …(2… …genomes.

Mostly bioinformatics, isn't it?

Author Contributions R.L., W.F., G.T., Ho.Z., L.H. and Jin.C. contributed equally to this work. Ju.W. and Ji.W. managed the project. Zhi.Z., R.H., F.S., He.Z., De.L., Ya.H., Jin.C., W.N., Jin.W. and W.W. prepared the panda DNA sample. X.Z., G.T., Jin.L., L.L., M.J., Da.L., Z.X., Jia.C., B.W., B.M., Z.W., Hu.L., X.R., Hu.Z., Si.L., Q.Z., Ju.Z., Y.R., Qin.L., Y.C., X.L. and Y.Z. performed sequencing. Ju.W., R.L. and W.F. designed analysis. Ho.Z., P.N., W.Q., G.S., S.Z., Run.L., F.T., J.R., M.Wa., Z.S., M.We., Xiao.W., H.W., L.X., T.-W.L. and S.-M.Y. performed genome assembly. Q.H., Q.C., Jia.L., J.M., Bi.L., Qib.L., Yu.H., Yang.Z., Ji.Z., W.G., X.X., Zu.L., X.S., Ho.L., D.Z. and Ni.Q. performed genome annotation. Ju.L., Bo.L., Y.B., Z.Y., S.C., Zha.Z., D.D., K.C., R.N., C.K., T.V., N.A., Sh.L., G.Z. and L.M. performed comparative genomics. Yap.Z., …W., F.W., Q.W., M.W.B., L.H., Y.S., Zh.L., C.C.S., O.A.R., F.C.-C.L., T.T.-Y.L., Y.W., …H., Y.F. and A.X. analysed genes related to panda-specific phenotypic characteristics. X.F., He.L., F.W., X.G., C.Yu., Hao.Z., Han.Z. and Y.L. identified heterozygous SNPs and performed panda historical population analysis. G.L., J.T., L.F., C.Ye. and T.G. performed data submission and database construction. Ju.W., Ji.W., R.L. and W.F. wrote the paper. X.W., G.Y., Y.G., Z.J., Juny.W., Na.Q., G.K.-S.W., L.B., M.O., K.K., So.L. and H.Y. revised the paper.

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LETTER

Natur **477**, 207 (2011)

doi:10.1038/nature10342

The genome sequence of Atlantic cod reveals a unique immune system

Bastiaan Star[1], Alexander J. Nederbragt[1], Sissel Jentoft[1], Unni Grimholt[1], Martin Malmstrøm[1], Tone F. Gregers[2], Trine B. Rounge[1], Jonas Paulsen[1,3], Monica H. Solbakken[1], Animesh Sharma[4], Ola F. Wetten[5,6], Anders Lanzén[7,8], Roger Winer[9], James Knight[9], Jan-Hinnerk Vogel[10], Bronwen Aken[10], Øivind Andersen[11], Karin Lagesen[1], Ave Tooming-Klunderud[1], Rolf B. Edvardsen[12], Kirubakaran G. Tina[1,13], Mari Espelund[1], Chirag Nepal[4,8], Christopher Previti[8], Bård Ove Karlsen[14], Truls Moum[14], Morten Skage[1], Paul R. Berg[1], Tor Gjøen[15], Heiner Kuhl[16], Jim Thorsen[17], Ketil Malde[12], Richard Reinhardt[16], Lei Du[9], Steinar D. Johansen[14,18], Steve Searle[10], Sigbjørn Lien[13], Frank Nilsen[19], Inge Jonassen[4,8], Stig W. Omholt[1,13], Nils Chr. Stenseth[1] & Kjetill S. Jakobsen[1]

Atlantic cod (*Gadus morhua*) is a large, cold-adapted teleost that sustains long-standing commercial fisheries and incipient aquaculture[1,2]. Here we present the genome sequence of Atlantic cod, showing evidence for complex thermal adaptations in its haemoglobin gene cluster and an unusual immune architecture compared to other sequenced vertebrates. The genome assembly was obtained exclusively by 454 sequencing of shotgun and paired-end libraries, and automated annotation identified 22,154 genes. The major histocompatibility complex (MHC) II is a conserved feature of the adaptive immune system of jawed vertebrates[3,4], but we show that Atlantic cod has lost the genes for MHC II, CD4 and invariant chain (Ii) that are essential for the function of this pathway. Nevertheless, Atlantic cod is not exceptionally susceptible to disease under natural conditions[5]. We find a highly expanded number of MHC I genes and a unique composition of its Toll-like receptor (TLR) families. This indicates how the Atlantic cod immune system has evolved compensatory mechanisms in both adaptive and innate immunity in the absence of MHC II. These observations affect fundamental assumptions about the evolution of the adaptive immune system and its components in vertebrates.

independently assembled bacterial artificial chromosome (BAC) insert clones (Supplementary Note 14 and Supplementary Fig. 9), and with the expected insert size of paired BAC-end reads (Supplementary Note 15 and Supplementary Fig. 10).

A standard annotation approach based on protein evidence was complemented by a whole-genome alignment of the Atlantic cod with the stickleback (*Gasterosteus aculeatus*), after repeat-masking 25.4% of the Newbler assembly (Supplementary Note 16 and Supplementary Table 6). In this way, 17,920 out of 20,787 protein-coding stickleback genes were mapped onto reorganized scaffolds (Supplementary Note 17). Additional protein-coding genes, pseudogenes and non-coding RNAs were annotated using the standard Ensembl pipeline. These approaches resulted in a final gene set of 22,154 genes (Supplementary Table 7). Comparative analysis of gene ontology classes indicates that the major functional pathways are represented in the annotated gene set (Supplementary Note 18 and Supplementary Fig. 11). We anchored 332 Mb of the Newbler assembly to 23 linkage groups of an existing Atlantic cod linkage map using 924 SNPs[8] (Supplementary Note 19 and Supplementary Table 8). These linkage groups have distinct orthology to chromosomes of other teleosts, on the basis of the number of co-

nature chemical biology

ARTICLE

PUBLISHED ONLINE: 18 SEPTEMBER 2011 | DOI: 10.1038/NCHEMBIO.662

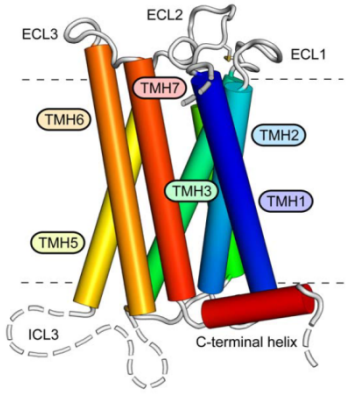
Ligand discovery from a dopamine D_3 receptor homology model and crystal structure

Try to do this without (bio)informatics skills?

Jens Carlsson[1,5], Ryan G Coleman[1,5], Vincent Setola[2,5], John J Irwin[1], Hao Fan[1,3,4], Avner Schlessinger[1,3,4], Andrej Sali[1,3,4], Bryan L Roth[2*] & Brian K Shoichet[1*]

G protein–coupled receptors (GPCRs) are intensely studied as drug targets and for their role in signaling. With the determination of the first crystal structures, interest in structure-based ligand discovery increased. Unfortunately, for most GPCRs no experimental structures are available. The determination of the D_3 receptor structure and the challenge to the community to predict it enabled a fully prospective comparison of ligand discovery from a modeled structure versus that of the subsequently released crystal structure. Over 3.3 million molecules were docked against a homology model, and 26 of the highest ranking were tested for binding. Six had affinities ranging from 0.2 to 3.1 μM. Subsequently, the crystal structure was released and the docking screen repeated. Of the 25 compounds selected, five had affinities ranging from 0.3 to 3.0 μM. One of the new ligands from the homology model screen was optimized for affinity to 81 nM. The feasibility of docking screens against modeled GPCRs more generally is considered.

GPCRs are a large family of membrane proteins that are critical for signal transduction. They have been a major focus of pharmaceutical research and are the primary targets of almost 30% of approved drugs[1]. All of these drugs were discovered without the aid of receptor structures by classical ligand-based medicinal chemistry. Accordingly, many of these drugs reflect their origins as mimics of natural signaling molecules. The determination of the first drug-relevant GPCR structures in the last 4 years[2–4] has opened up opportunities for structure-based discovery of more



Read this article as part of the curriculum!

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Structural Bioinformatics

No wet lab biology?

Biology's Dry Future

The explosion of publicly available databases housing sequences, structures, and images allows life scientists to make fundamental discoveries without ever getting their hands "wet" at the lab bench

Most life scientists single-mindedly focus their careers on a particular organism or disease—even just a specific molecular pathway. After all, it can often take months of training to master growing a particular cell type or learn a new laboratory technique. Atul Butte, however, wanders from topic to topic—and reaps scientific successes along the way. Though only 44 years old, he has earned tenure at Stanford University's School of Medicine in Palo Alto, California, based on advances in diabetes, obesity, transplant rejection, and the discovery of new drugs for lung cancer and other diseases.

Butte's lab is different, too. It isn't crowded with cell cultures and reagents. His tools look like those of an engineer or software developer: Most often, he's simply working on a Sony laptop, although at times he does turn to a large computer cluster at Stanford and supercomputers elsewhere when in need of massive processing power. Instead of growing cells and sequencing DNA, Butte, his students, and postdocs sift through massive databases full of freely available information, such as human genome sequences, cancer genome readouts, brain imaging scans, and biomarkers for specific diseases such as diabetes and Alzheimer's.

Many call this type of research "dry lab biology," to contrast it with the more hands-on "wet" traditional style of research. Although statistics on the number of dry lab biologists are hard to come by, these data hunters believe they are a growing minority. Butte is one of its top practitioners. Using publicly available data, for example, 2 years ago Butte and his colleagues surveyed the activity of large sets of genes in people affected by 100 different diseases and in cultured human cells exposed to 164 drugs already on the market. By comparing patterns of genes flipped on or off by the diseases and by the drugs, the team drew unexpected connections. They found clues

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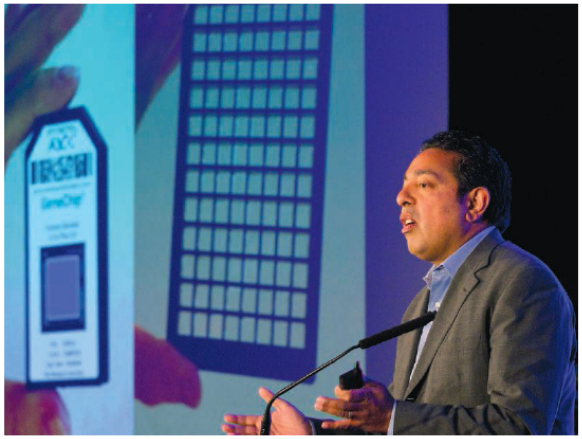


"I'm like a **kid in a candy store**. There is so much we can do."

—Atul Butte, Stanford University School of Medicine

Science, **342**, 186 (2013)

Exome sequencing detects disease-causing SNVs and CNVs in Primary Immunodeficiencies

Hanne Sørmo Sorte, PhD student

Department of Medical Genetics

Oslo University Hospital and University of Oslo

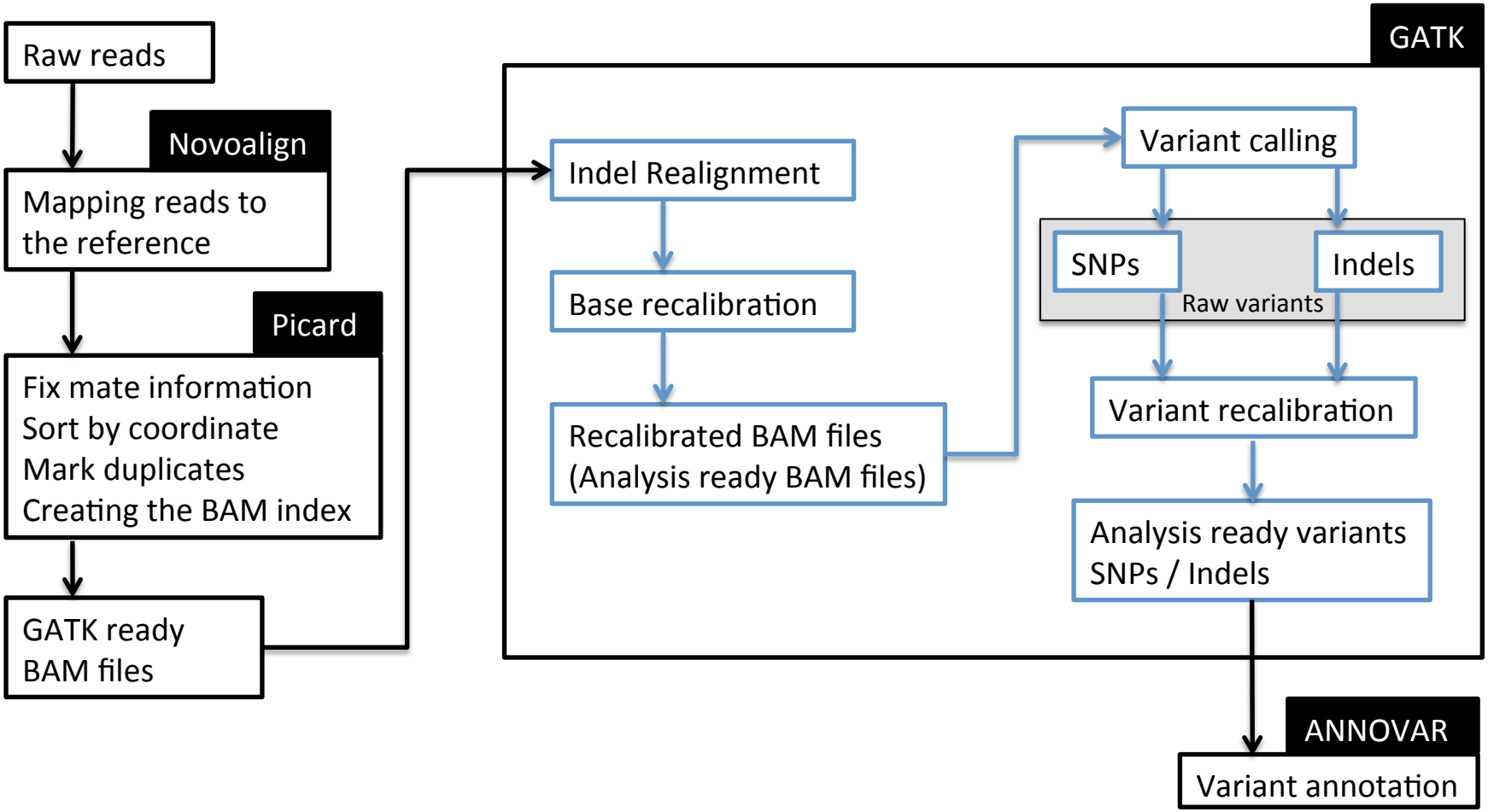
Oslo, Norway

Oslo University Hospital

UiO : University of Oslo

- Mapping to the reference genome
- IGV: Visualization tool – chromosome w/ tracks ex RefSeq genes
- Exonic/intronic/intergenic regions

Bioinformatics

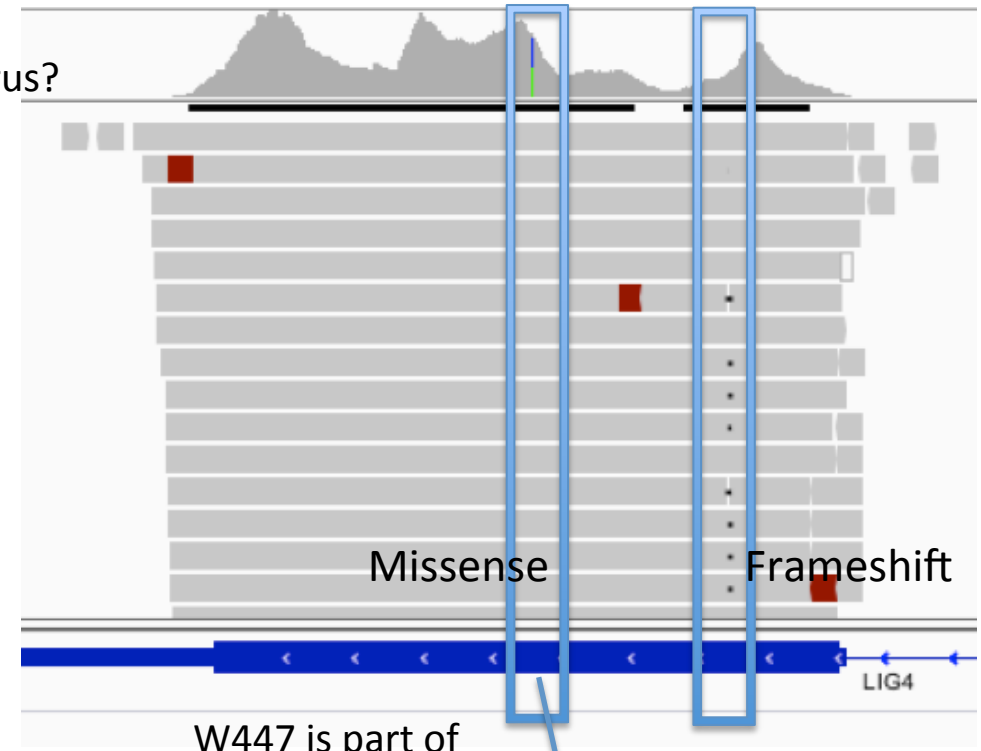


Solved case - example of clinical utility

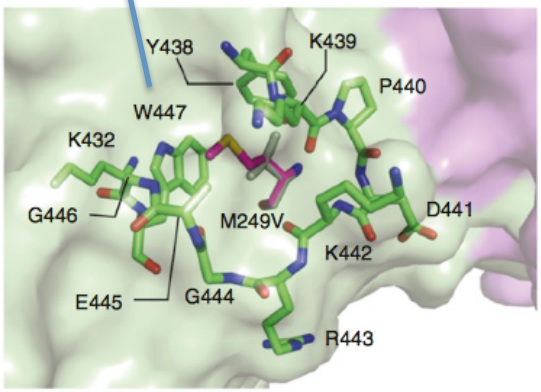
- 4 year old boy, healthy until 2 ½
- Feb -13: Anemia and thrombocytopenia – virus?

  normal lymphocytes/IgG
- Apr-13:
  - respiratory distress ->
  - OUS: pneumocystis pneumonia
  - $T^{low}B^{-}NK^{+}$ + low IgG – treated
  - Chronic Rota virus + parvoB19

    – not able to cure
- Fall -13: falling T-cell - develop full but untypical immunodeficiency ->
  - Specific genetic tests negative
  - HSCT transplantation?
  - Pretreatment conditioning
- Exome sequencing: LIG4 (DNA ligase IV)
  - impaired DNA ds break rejoining
  - Few reported; different presentation



W447 is part of the catalytic pocket



Confirmed by radiosensitivity assay -> HSCT w/correct preconditioning -> Now completely healthy!!

Database

- Organized collection of data/information, in computer-readable form
- Defining characteristics
  - the contents
  - the ontology (list of valid terms and their definition, vocabulary)
  - logical structure (interrelationship among the data)
  - data format
  - routes for data retrieval, data presentation or analysis
  - links to other databases, references to original publication data etc.

A.M. Lesk, *Introduction to Bioinformatics*

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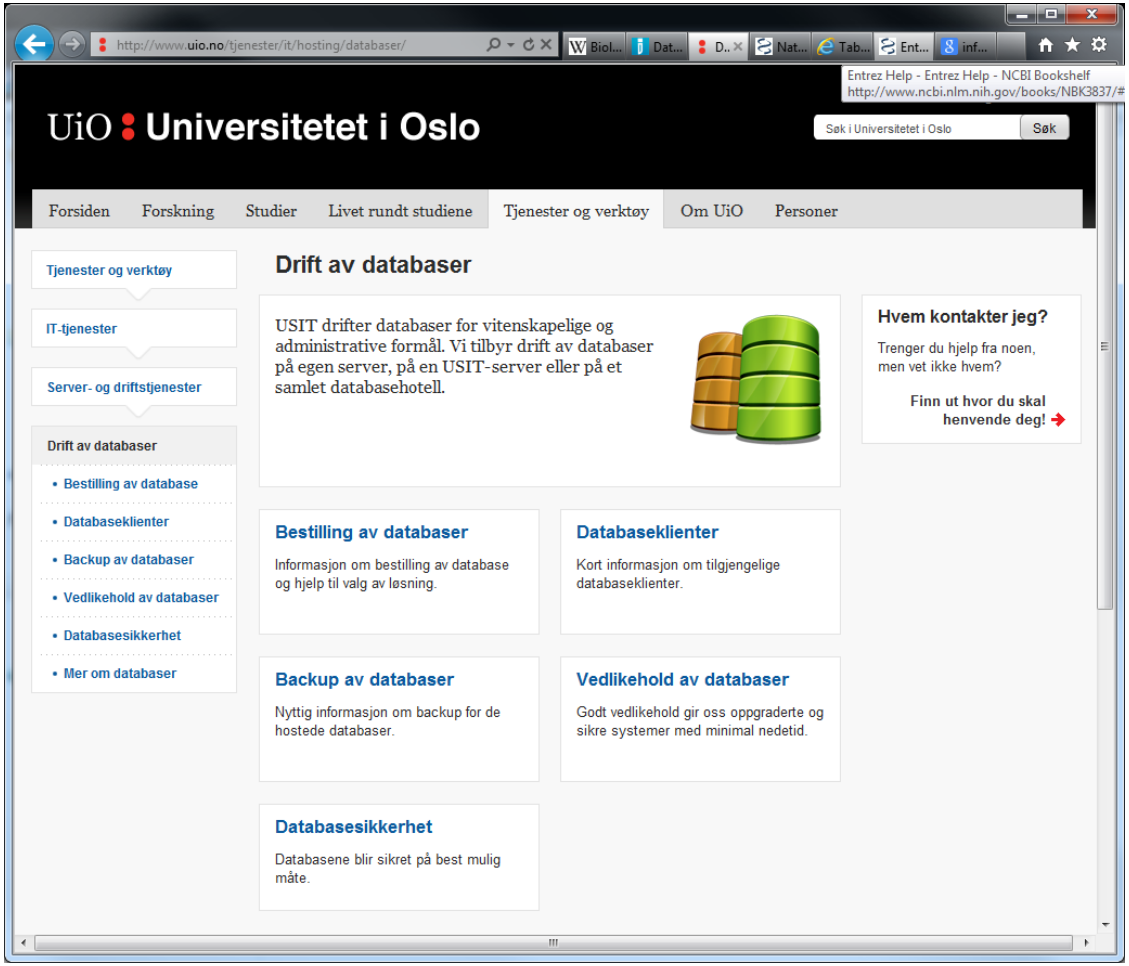
Making your own database?

Talk to an informatician! (or USIT at UiO)



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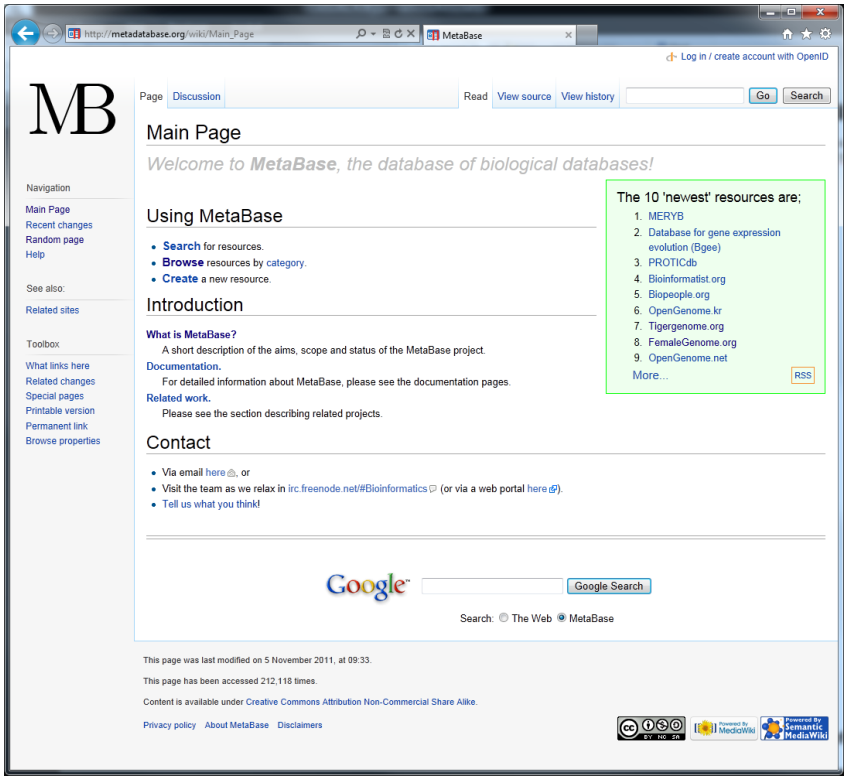
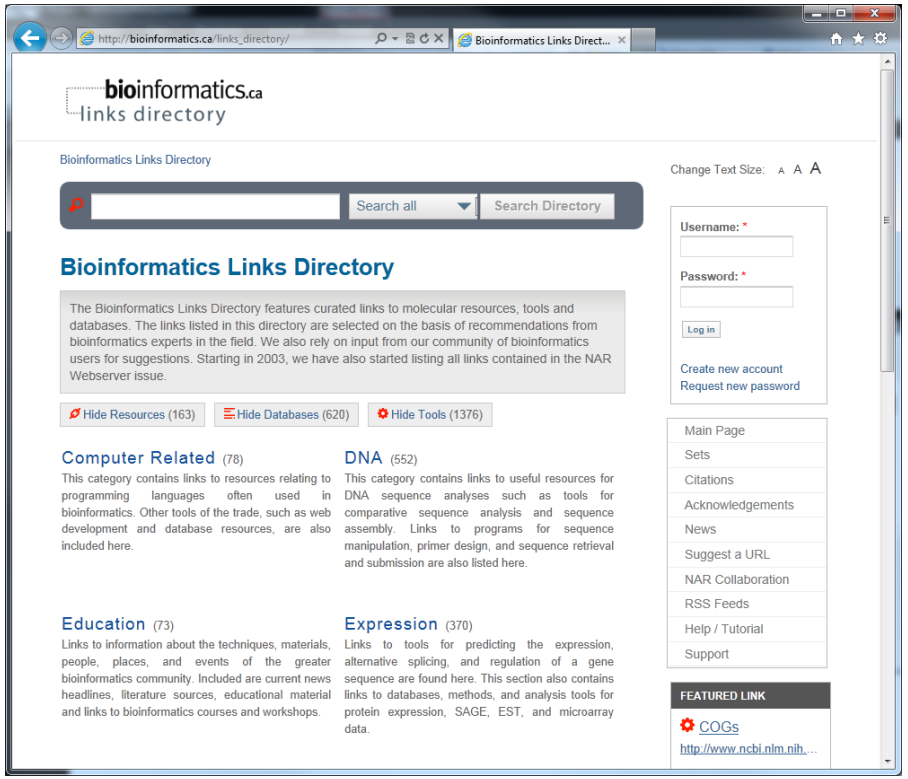
A lot of biological databases already available...





MetaBase, the database of biological databases (1800 entries)
- http://metadatabase.org

bioinformatics.ca – links directory (623 databases)
- http://bioinformatics.ca/links_directory

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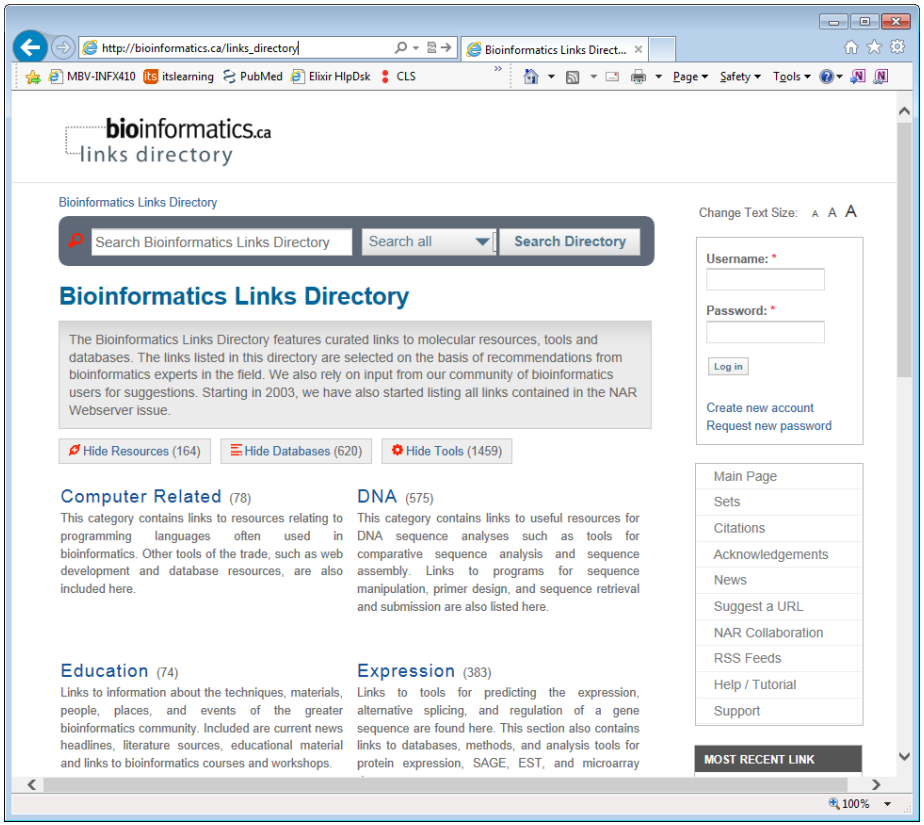
btw, the **bio**informatics.ca links directory is an excellent resource



bioinformatics.ca – links directory

- http://bioinformatics.ca/links_directory
- Currently
  - 1549 tools
  - 623 databases
  - 174 “resources”
- The problem is not to find a tool or database, but to know what is “gold” and what is “junk”

Some important centres for bioinformatics

- National Center for Biotechnology Information (NCBI)
  - part of the US National Library of Medicine (NLM), a branch of the National Institutes of Health
  - located in Bethesda, Maryland
- European Bioinformatics Institute (EMBL-EBI)
  - part of part of European Molecular Biology Laboratory (EMBL)
  - located in Hinxton, Cambridgeshire, UK

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NCBI databases

- Provided the GenBank DNA sequence database since 1992
- Online Mendelian Inheritance in Man (OMIM) - known diseases with a genetic component and links to genes
  - started early 1960s as a book
  - online version, OMIM, since 1987
  - on the WWW by NCBI in 1995
  - currently >22,000 entries (14,400 genes)
- EST - nucleotide database subset that contains only Expressed Sequence Tag records
- Gene - genes and associated information for a number of organisms in addition to and including human
- Protein sequence database - collection of protein sequence entries compiled from a variety of sources including Swiss-Prot, PIR, PRF, PDB, and translations from annotated coding regions in GenBank and RefSeq
- PubMed - access to over 15 million citations from MEDLINE and additional life sciences journals
- SNP - repository for both single nucleotide substitutions and short deletion and insertion polymorphisms

All data is publicly available

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NCBI databases

Table 1. The Entrez Databases (as of September 1, 2012)

Database	Section within this article	Records	Data source
Site search	Introduction	10 686	N
Assembly	Recent developments	9597	D, C, N
PubMed	Literature	22 076 132	C
PubMed central	Literature	2 523 284	D, C
NLM catalog	Literature	1 461 835	C, N
MeSH	Literature	236 253	N
Books	Literature	186 112	C, N
Taxonomy	Taxonomy	932 345	C, N
EST	DNA and RNA	73 666 909	D (GenBank)
Nucleotide	DNA and RNA	66 319 706	D (GenBank), C, N
GSS	DNA and RNA	34 533 114	D (GenBank)
BioSample	DNA and RNA	970 304	N
SRA	DNA and RNA	228 739	D
PopSet	DNA and RNA	159 345	D (GenBank)
Protein	Proteins	56 394 380	C, N
Protein clusters	Proteins	794 663	N
GEO profiles	Genes and expression	63 811 486	D
Probe	Genes and expression	14 248 527	D
Gene	Genes and expression	11 290 372	C, N
UniGene	Genes and expression	5 831 327	N
GEO data sets	Genes and expression	841 518	N
Biosystems	Genes and expression	396 029	C
Homologene	Genes and expression	133 012	N
Clone	Genomes	29 597 231	D, N
UniSTS	Genomes	545 353	D (dbSTS)
BioProject	Genomes	58 227	D
Genome	Genomes	8276	C, N
Epigenomics	Genomes	5484	D
SNP	Genetics and medicine	162 674 947	D (dbSNP), N
dbVar	Genetics and medicine	2 729 616	D
dbGaP	Genetics and medicine	143 624	D
Online mendelian inheritance in animals	Genetics and medicine	2810	C
PubChem substance	Chemicals and bioassays	100 157 112	D
PubChem compound	Chemicals and bioassays	35 545 766	N
PubChem bioassay	Chemicals and bioassays	621 642	D
Structure	Domains and structures	83 913	C, N
CDD	Domains and structures	46 389	C, N

D, direct submission; C, collaboration/agreement; N, internal NCBI/NLM curation.

37 databases that together contains over 690 million records

Nucleic Acids Res. **41**, D8 (2013)

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EMBL-EBI databases

- European Nucleotide Archive (ENA) nucleotide sequence database
- Ensembl - automatic and manually curated annotation on selected eukaryotic (vertebrate) genomes
- Ensembl Genomes – Ensembl for “all other organisms”
- UniProt – protein sequence and functional information
- ChEMBL – database of bioactive compounds
- IntAct - repository of molecular interactions, including protein-protein, protein-small molecule and protein-nucleic acid interactions
- CiteXplore – 25 million literature abstracts including PubMed, Agricola & patents
- Gene Ontology (GO) - controlled vocabulary to describe gene and gene product attributes in any organism
- Gene Ontology Annotation (GOA) – GO annotations for proteins in UniProt

GenBank

- a comprehensive public database of nucleotide sequences and supporting bibliographic and biological annotation
- *all* publicly available DNA sequences
- submissions from authors
  - web-based BankIt
  - standalone program Sequin
- submissions from EST and other high-throughput sequencing projects
- daily exchange of data with ENA and DNA Data Bank of Japan (DDBJ)
  - all sequences submitted to DDBJ, ENA, or GenBank will end up in all 3 databases within few days

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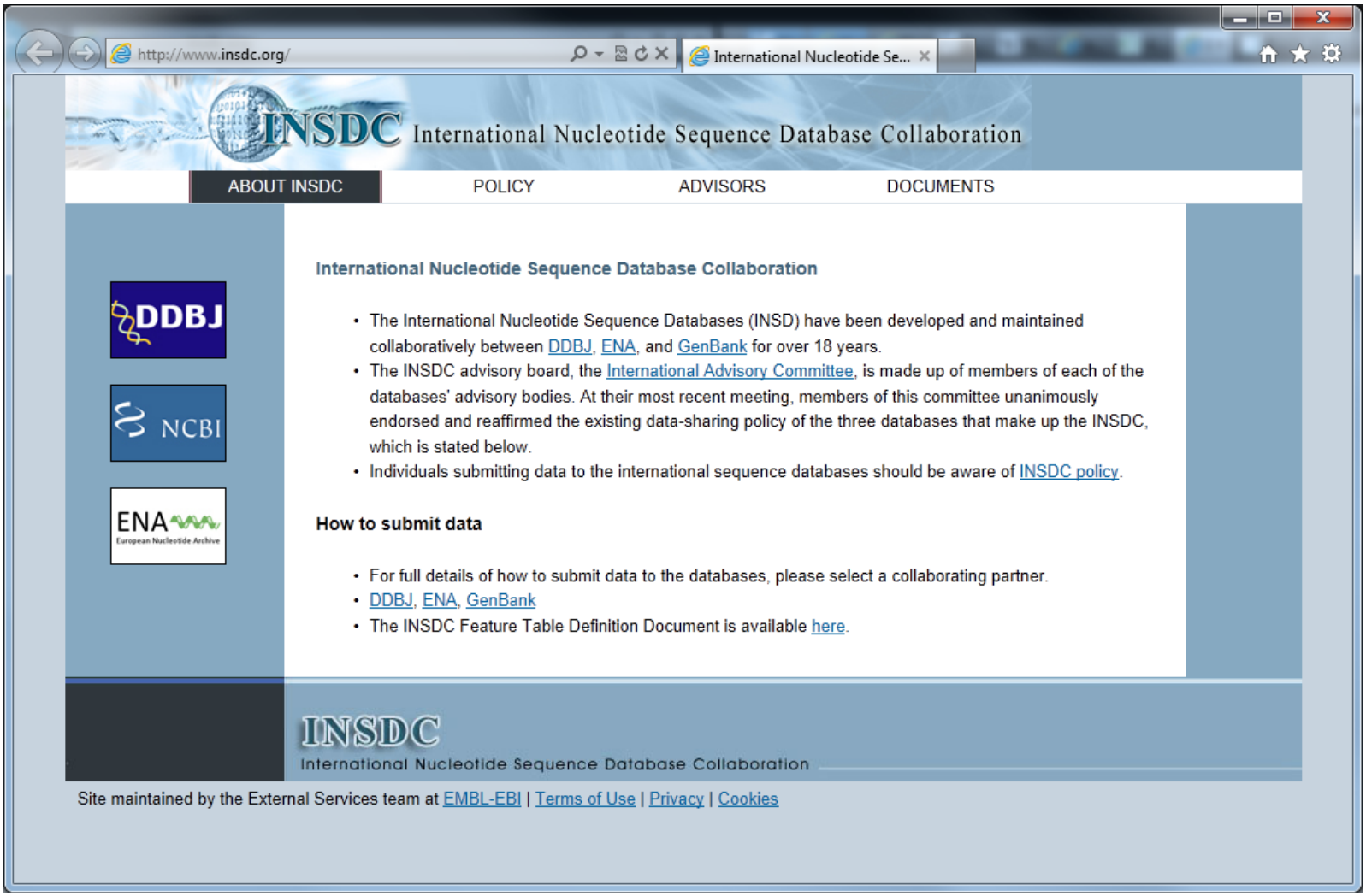
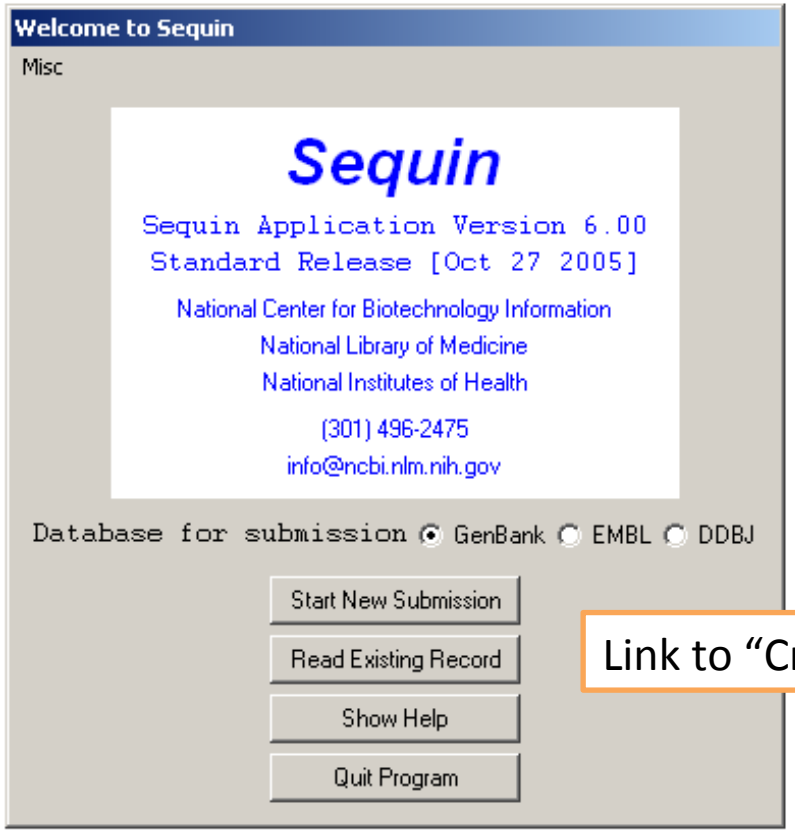
INSDC



Sequin – for submitting to GenBank



BankIt is web-based alternative

Link to “Create a submission”

```
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ACCESSION   Y09687
VERSION     Y09687  GI:1772973
KEYWORDS    endonuclease III; homologue; NTH1.
SOURCE      Homo sapiens (human)
  ORGANISM  Homo sapiens
            Eukaryotae; mitochondrial eukaryotes; Metazoa; Chordata;
            Vertebrata; Eutheria; Primates; Catarrhini; Hominidae; Homo.
REFERENCE   1  (bases 1 to 1030)
  AUTHORS   Rognes,T.
  TITLE     Direct Submission
  JOURNAL   Submitted (28-NOV-1996) T. Rognes, University of Oslo, Institute of
            Medical Microbiology, The National Hospital, N-0027 Oslo, NORWAY
REFERENCE   2  (bases 1 to 1030)
  AUTHORS   Luna,L., Bjoras,M., Rognes,T., Hoff,E. and Seeberg,E.
  JOURNAL   Unpublished
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                     ATLGKLIYPVGFWRSKVKYIKQTSAILQQHYGGDIPASVAELVALPGVGPKMAHLAMA
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                     GQQTCLPVHPRCHACLNQALCPAAQGL"
ORIGIN
        1 acgagcgcct tgagcgcgag gatgctgacc cggagccgga gcctgggacc cggggctggg
       61 ccgcgggggt gtagggagga gcccgggcct ctccggagaa gagaggctgc agcagaagcg
      121 aggaaaagcc acagccccgt gaagcgtccg cggaaagcac agagactgcg tgtggcctat
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      361 taccaggtgc tgctgtcact gatgctctcc agccaaacca aagaccaggt gacggcgggc
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      841 tgtctgcctg tgcaccctcg ctgccacgcc tgcctcaacc aagccctctg cccggccgcc
      901 cagggtctct gatggccgca tggctctggc cgaggtgccg ctgtggccac cgtctgtgaa
      961 gtggctttac gcttcaggaa gccacgcctg ttgaataaag ctttggtgtg tttgcaaaaa
     1021 aaaaaaaaaa
//
```

Entry in GenBank format

April 2011:

- 126,551,501,141 bases in 135,440,924 sequence records in the traditional GenBank divisions
- 191,401,393,188 bases in 62,715,288 sequence records in the WGS

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Growth of GenBank

Table 1. Growth of GenBank divisions (nucleotide base pairs)

Division	Description	Release 191 (8/2012)	Annual increase (%)[a]
Taxnomic divisons			
SYN	Synthetic	928 200 038	494.2%
PHG	Phages	84 079 451	34.4%
ENV	Environmental samples	3 374 433 548	32.1%
VRL	Viruses	1 429 464 786	21.1%
BCT	Bacteria	8 439 854 434	21.0%
PLN	Plants	5 481 470 133	15.6%
MAM	Other mammals	863 036 872	6.9%
VRT	Other vertebrates	2 886 594 595	6.7%
PRI	Primates	6 317 656 773	3.3%
UNA	Unannotated	127 803	1.5%
ROD	Rodents	4 435 106 948	0.9%
INV	Invertebrates	2 493 058 927	−1.7%
Functional divisions			
TSA	Transcriptome shotgun data	5 759 588 580	207.3%
WGS	Whole-genome shotgun data	308 196 411 905	47.9%
PAT	Patented sequences	12 118 622 726	8.6%
GSS	Genome survey sequences	21 947 780 105	5.7%
EST	Expressed sequence tags	40 888 051 100	4.8%
HTG	High-throughput genomic	24 359 210 558	0.1%
STS	Sequence tagged sites	636 262 446	0.1%
HTC	High-throughput cDNA	639 165 410	−3.5%
TOTAL	All GenBank sequences	451 278 177 138	33.1%

[a]Measured relative to Release 185 (8/2011).

New release frequency: 2 months

Current release is 204 (Oct, 2014)

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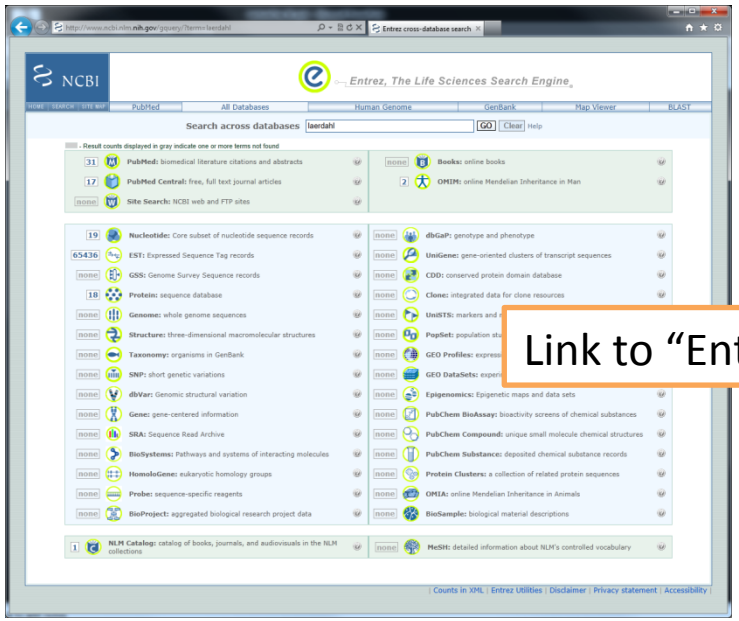
NCBI Entrez retrieval system

- Entrez is the most widely used interface for information retrieval from the NCBI databases
  - search engine
  - web portal
  - global query of all (35?) NCBI databases



Link to “Entrez” and search for “Laerdahl”