

Insights from integrative analysis of the C. elegans genome:

What approaches we learned that were applicable to annotating the human genome

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> > Slides at

Lectures.GersteinLab.org (See Last Slide for References & More Info.)





# **2** Approaches to Genome Annotation



# Importance of Dark Matter of the Genome

- Non-coding regions contain the control elements for coding regions.
- Some non-coding regions are functional & are pervasively transcribed.
- "Molecular Fossils" in the non-coding genome represent a historical record of the genome
- Most disease-associated mutations (e.g. GWAS hits) are in non-coding regions.

[Gravitational lensing by dark matter in Abell 1689 – HST (NASA, ESA)]

# **Overview of the Data**

### • Worm

- Dev. Timecourse:E, L1, L2, L3, L4 + more
- RNA-seq on timecourse + extra stages (polyA, small-RNA, 3' UTR selected)
- Total RNA Tiling Arrays on timecourse + tissues
- Chip-seq : 22 TFs + Pol2 in a variety of stages
- Chromatin Chip-chip :
  >12 HMs mostly in EE & L3

# Human (very briefly!)

- ~200 tot. cell lines
  with lots on tier 1
  (GM12878, K562, H1)
- ~120 TFs
- deep RNA-seq
- ~12 main HMs (chip-seq)

# Expression Timecourse Analysis

Coordinated binding & expression; E v L separation;
 ~280 large splicing changes

# ncRNAs [Hum]

- Importance of evidence integration
- Large numbers of transcribed pseudogenes (8-15%)
- Chromosomal activity distribution [Hum]
  - Most constrained regions active
  - Repressed arms & binding HOT spots.

# Regulatory Net [Hum]

- Arranging TF binding into a hierarchy with differences betw. levels.
   Integration with miRNA regulation (more at top).
- Network motifs & prevalence of FFLs
- Stat Models relating HMs, TFs & Expression [Hum]
  - HMs statistically predict expression for protein-coding genes and miRNAs
  - Similar results for TFs, highlighting predictive power of a few TFs.
  - Chromatin model (+ PWM) effective in predicting TF sites
    - -- useful in identifying enhancers.

Dynamics of Correlated Expression Changes Changes over Timecourse



0.40.4

Dynamics of Correlated Expression & Pol2 Binding Changes Changes over Timecourse





# Splicing Changes over the Timecourse (~280 changes/pair-of-stages)



10

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# Identification of many candidate ncRNAs through evidence integration

- ~7k candidates
- No single feature (e.g. expr. expts., conservation, or sec. struc.) finds all known ncRNAs => combine features in stat. model
- 90% PPV, 13 of 15 tested validate





Gold-standard Set

# One type of ncRNA: Transcribed Pseudogenes



- 1198 total pseudogenes
- 194 (16%) have strong evidence of independent transcription

[Science 330:6012]

# Different Tissues in Body Map

# Human ncRNAs and Pseudogene Transcription

- Gencode 10 : manual annotation
   + a variety of pipelines
  - -~5500 lincRNAs
  - 11216 high-qual.
    pseudogenes
    (from ~14K total)
    - Total transcribed pseudogene: 876 (RTPCR validated: 57 of 76)



### Parent: ENSG00000176444.13

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# **Conservation of Functional Elements: Most Constrained Bases are Annotated**





# **HOT regions of clustered binding**



log<sub>2</sub>(gene expression)

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# **Worm TF Hierarchy & Gene Properties**



- ~25K edges
- Top: more tissue specific & HOX (& more miRNA reg.)
- Bottom: more essential
- Stats weak but pattern consistent with that in yeast, human...

# **Relating Worm TF Hierarchy with miRNAs**



[*Science* 330:6012]





Human: Strongest Proximal Regulatory Edges Can be Arranged into a Hierarchy

Optimally arrange TFs into 3 levels by sim. annealing, maximizing downward-pointing edges



Integration of TF hierarchy with other 'omic information : more influential & connected TFs on the top



#### Network Motif Analysis: **Enrichment of FFLs** 6 pairs of toggle switches $\sim \rightarrow \circ$ 3-node motifs Ő Ō **O**← O O⇔O О O Ο O С $\Box$ О $\Box$ О $\mathbf{C}$ О 868 490 729 26 Freq. 0 0 8 64 6 6 2 16 122 (0.84)(0.70) (1.8) (2.9)(4.8)(0.81)(0.72)(0.62)(0)(0)(0.91)(5.6)(1.4)Ν 3500 3000 2500 2000 1500 1500 1000 500 0 Т Μ В

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# Modeling Transcription: Connecting Inputs & Outputs

- Models
  - HMs+TFs => gene expression
  - -HMs => TFs



# His. mods around TSS are related to level of gene expression



# **Histone Modification model**



# His. mods around TSS & TTS are clearly related to level of gene expression, in a position-dependent fashion



[Science 330:6012] [Related work: Ouyang et al. ('09) PNAS; Karlic et al. ('10) PNAS]

# Integrate all histone modifications to predict gene expression levels



 $\star = LOG_{10}RPKM$ 



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Modeling with Worm TFs: Positive and negative regulators from correlating TF signal at TSS with gene expression





### Relative importance of TFSCAGE PolyA+ K562 Whole Cell



 Model with only a few of the 1000s of total TFs is able to predict well



 Different Regions of Influence for TFs vs HMs

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# Chromatin model: link histone modification patterns to TF binding







Identifying Potential Enhancer-like Elements from Discriminative HM Model & then Linking these to Targets (via cell-line correlations) to Create Distal Edges



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# Comparing

# **Proximal**

# &

Distal

**Networks** 

[

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