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Because of

[16] M. Imakaev, G. Fudenberg, R. P. McCord, N. Naumova, A. Goloborodko, B. R. Lajoie, J. Dekker, and L. A.

Mirny. Iterative correction of Hi-C data reveals hallmarks of chromosome organization. Nat Methods, 9:999–

1003, 2012.

[17] M. Hu, K. Deng, S. Selvaraj, Z. Qin, B. Ren, and J. S. Liu. HiCNorm: removing biases in Hi-C data via

Poisson regression. Bioinformatics, 28(23):3131–3133, 2012.

[18] A. Cournac, H. Marie-Nelly, M. Marbouty, R. Koszul, and J. Mozziconacci.

Normalization of a chromosomal

contact map. BMC Genomics, 13:436, 2012.

[19] W. Li, K. Gong, Q. Li, F. Alber, and X.J. Zhou. Hi-Corrector: a fast, scalable and

memory-efficient package

for normalizing large-scale Hi-C data. Bioinformatics, 31(6):960–962, 2015.

[20] Ei-Wen Yang and Tao Jiang. GDNorm: An improved poisson regression model for reducing biases in Hi-C

data. In Proceedings of the 14th International Workshop of Algorithms in Bioinformatics, volume 8701 of

Lecture Notes in Computer Science, pages 263–280, Berlin, Heidelberg, 2014. Springer-Verlag.

[21] Yoli Shavit and Pietro Lio'. Combining a wavelet change point and the bayes factor for analysing chromoso-

mal interaction data. Mol. Biosyst., 10(6):1576–1585, 2014.

A key continuing role

The DAC will set up a

Another important responsibility of the DAC in writing consortium papers is connecting

data,

stay as truthfully as possible to the

lab effect

(except that TF peaks are bigger, several hundred bps).

cell types. These datasets are at 40 kb

to minimizing batch effects that may be caused by differences among production centers.

, 2006 16719718}. Active

computational efforts in predicting enhancers by integrating

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a two -label annotation

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The DAC[1] recently evaluated correlation-based methods using the capture Hi-C data on GM12878 cells {Mifsud 2015 NG PMID: 25938943}

The DAC will continue to evaluate existing methods. In addition, we will also

Page 51: [85] Deleted Author 3/20/16 4:55 PM

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+purcaro@gmail.com Michael can you make one file out of the panels in this figure? Please make sure to preserve the quality. You need to put a "d" label in the middle panel, and change ABCDEF to efghij for the right panel. Thanks!

Page 55: [88] Comment [39] William Stafford Noble 3/17/16 10:50 PM

[50] J. Edmonds. Matroids, submodular functions, and certain polyhedra. Combinatorial Structures and Their

Applications, pages 69–87, 1970.

[51] L. Lovasz. Submodular functions and convexity. In M. Grotchel A. Bachem and B. Korte, editors, Mathemat-

ical Programming – The State of the Art, pages 235–257. Springer-Verlag, 1983. [52] A. Schrijver. Combinatorial Optimization. Springer, 2004.

[53] H. Narayanan. Submodular functions and electrical networks. Annals of Discrete Mathematics, 54, 1997.

[54] G. Cornunejols, G. L. Nemhauser, and L. A. Wolsey. The uncapacitated facility location problem. In P.B.

Mirchandani and R.L. Franci, editors, Discrete Location Theory, chapter 3. Wiley/Interscience, New York,

1990.

[55] M. Narasimhan and J. Bilmes. A submodular-supermodular procedure with applications to discriminative

structure learning. In Uncertainty in Artificial Intelligence (UAI), Edinburgh, Scotland, July 2005. Morgan

Kaufmann Publishers.

[56] A. Krause, A. Singh, and C. Guestrin. Near-optimal sensor placements in gaussian

processes: Theory,

efficient algorithms and empirical studies. The Journal of Machine Learning Research, 9:235–284, 2008.

[57] Y. Liu, K. Wei, K. Kirchhoff, Y. Song, and J. Bilmes. Submodular feature selection for high-dimensional

acoustic score spaces. In Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International

Conference on, pages 7184–7188. IEEE, 2013.

[58] Kai Wei, Yuzong Liu, Katrin Kirchhoff, Christopher Bartels, and Jeff Bilmes. Submodular subset selection

for large-scale speech training data. In Acoustics, Speech and Signal Processing (ICASSP), 2014 IEEE

International Conference on, pages 3311–3315. IEEE, 2014.

Here are these cites: [57] Y. Liu, K. Wei, K. Kirchhoff, Y. Song, and J. Bilmes. Submodular feature selection for high-dimensional

acoustic score spaces. In Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International

Conference on, pages 7184–7188. IEEE, 2013.

[62] B. Mirzasoleiman, A. Karbasi, R. Sarkar, and A. Krause. Distributed submodular maximization: Identifying

representative elements in massive data. In Advances in Neural Information Processing Systems, 2013.

[63] R. Gomes, A. Krause, and P. Perona. Discriminative clustering by regularized information maximization. In

Advances in Neural Information Processing Systems, 2010.

[64] M. Libbrecht, M. M. Hoffman, J. A. Bilmes, and W. S. Noble. Entropic graph-based posterior regularization.

In Proceedings of the International Conference on Machine Learning, Lille, France, 2015.

We will adopt the current chairing structure of the AWG calls (where the leaders are appointed by the NHGRI).

Integration of production efforts**.** We will

Old Section 3:

keeppar The wealth of data from the ENCODE Project will lead to biological insights only if well-defined analyses are performed with appropriate computational
thods in a reasoned priority. The large number of possible anal methods in a reasoned priority. The large number of possible analyses could lead to confusion or even stagnation if not prioritized wisely. Thus, the design of the
DAC has placed a strong emphasis on posing questions that requirements, time-lines, etc. The DCC and data producers also play important roles in selecting the questions. The AWG includes other members, such as the production PIs, bioinformatics members of the production groups, members of the U01 groups interested in participating in integrative analysis, and other
informatics groups loosely associated with the Consortium. The DAC w producers, and to some extent with the computational groups funded by the U01s. The types and details of the analyses will be determined during the course of the project, and we provide example analyses throughout this proposal.

,,,nokeep The interactions among AWG, DAC, DCC, production groups, and interested U01-funded analysis groups are best explained in the context of the entire
work-flow for DAC, from experimental data through to analysis r group, e.g., peak finding in ChIP-seq data and transcript identification in RNA-seq data. The DAC aims to establish specific contacts with the bioinformaticians in each production group and the DCC, in order to keep up-to-date with the nuances of the specific data types which can benefit integrative analysis. Furthermore,
the DAC can assist the primary analysis in several ways: contr

eeppar Moving beyond the primary data processing, the main source of work will be biological questions or analysis directions posed by the AWG. The DAC leadership committee (Profs. Weng, Kellis, and Gerstein) will assign them to a group for investigation and determination of whether there are existing methods that
have both appropriate statistics and are scalable to genom type of the analysis, the results will be reported either as data integrated into the genome browser and/or a new pipelined approach provided for regular use by all users, in particular other members of the ENCODE Consortium.

For some questions, new statistical methods are required as some existing methods do not scale for genome-wide datasets. We may be able to draw upon the
strengths of some U01 groups. An example is Prof. Peter Bickel or Pro the analysis. For other questions, we will create a small group of DAC members to focus on the problem, in many cases starting with developing new statistical methods, followed by algorithmic/engineering analysis for genome-wide scalability. The statistical methods are likely to be novel applications of the broad
collection of statistical and machine-learning tool kits, but the bioinformaticians, and biologists. Once a new method has been successfully created and scales well, this method can then be appropriately pipelined. Some problems will require us to recruit expertise outside the Consortium. We have established a procedure to invite outside investigators to join the AWG and fund some of their efforts through the DAC (see the PI Leadership Plan).

We expect to quickly have more tasks than resources, in particular because we expect to have a steady flow of tasks to change existing ad hoc analysis schemes
into methods that can either be pipelined or provided as end-us will schedule our work in a completely transparent manner, with any priority disputes being resolved, and with the AWG having the final say on priorities. Figure XXX outlines the management of the prioritized list of tasks being performed by the DAC.

,,,,,keeppar As in the current phase of ENCODE, we will organize a weekly conference call for the entire AWG. The call at the beginning of each month will be
open to any member of the Consortium and used to report progress provide estimates on the relative "cost" of each task, and the optimal groups to handle each task. New tasks are generated by the AWG and by DAC members suggesting new pipelining or engineering approaches to make existing ad hoc methods more robust. Although the DAC members can suggest tasks and obviously
must be involved in the assessment of matching tasks to groups, we w Consortium needs.

The DAC will ensure openness by inclusiveness in its working practices and a formal prioritization process from the AWG. To ensure inclusiveness the DAC will conduct all meetings in formats that allow any ENCODE Consortium member to join and participate as equal members in the analysis. The progress of analysis will be posted on the ENCODE Wiki, again allowing complete access by other Consortium members. The progress of DAC analysis tasks will be
reviewed and future priorities set in an open forum with the AWG and rel arbiter of any priority dispute. DAC members will be available, given practicalities, for any AWG-proposed meeting. AWG phone calls will be chaired by the three
members of the DAC leadership committee, with the three membe

The members and leadership of the proposed DAC recognize that the proposed work flow and management is quite different than the usual mode of working on investigator-initiated projects. The DAC will be responsive to a wide range of inputs, with problems defined and prioritized by the AWG, close coordination with the DCC, and inclusion of other members of the ENCODE Consortium and others with needed expertise. We will organize annual data analysis workshops to bring together researchers from both inside and outside of the Consortium including the data producers, experts in data analysis, and experts in the biology of different
classes of functional elements for face-to-face interactio and experience of the DAC members will be weighed favorably as the AWG establishes priorities. Indeed, this community-based approach to problem solving will
be exciting and lead to insights that may not be obtained in stud various entities in and beyond the ENCODE Consortium:

AWG: DAC members are active participants of the AWG, and the goal of the DAC is to perform and facilitate the analyses defined by the AWG. The DAC will
assist the AWG in defining and prioritizing the tasks, performing the disseminating analysis results.

Production groups and U01 groups: A challenge in the AWG will be to coordinate between the diversity of groups participating in analysis, and to ensure not only that each planned analysis is successfully completed, but also that there is minimal replication of effort between different groups. Achieving these goals will require
constant communication between the different members o coordinate analysis goals, plan deliverables, establish milestones, and ensure that different groups build on each other's results. In particular, we will work with the Pls of the production groups who are ideally situated for understanding the subtleties of their datasets to establish optimal protocols, sequencing depth, and
number of biological and technical replicates, and agree upon u particularities of each data type. We will also work with the PIs of the production groups to establish goals for integrative analysis, and the specific integration plan for each type of data, interpret the analysis results, and adjust analysis goals based on their biological interpretation.

DCC: The DAC and DCC components of the EDCAC will work together on several issues, with five examples listed here. (1) Perform uniform primary processing of datasets and establish a single processing pipeline to be run by the DCC component on all datasets; (2) Establish uniform naming schemes for all datasets, a
transparent directory structure, and ways to access the datase and posting individual datasets; (4) Build a common computing platform for running common tools on all datasets; and (5) Disseminate the analysis results of the DAC.

NHGRI: On a regular basis, the DAC will update the ENCODE Consortium and the NHGRI on the progress towards completion of the comprehensive catalog of al elements. We will also provide quarterly reports that will allow assessment of progress towards achieving DAC goals.

Additional informatics groups outside the Consortium: We will identify areas of expertise not represented in the AWG, and will invite outside investigators to join
AWG analyses when necessary. We have specifically budgeted

<mark>[[eut this b/c it's in 1.7]]</mark> Other large consortia and outside production groups with complementary datasets: In addition to the ENCODE project, several large
consortia are involved in systematic data generation activiti work with individual labs that systematically generate large-scale datasets of significant value to the ENCODE Project, based on the priorities set forth by the AWG, the ENCODE PIs and co-PIs, and the NHGRI.

3.2 Provide shared computational guidelines and infrastructure for data processing, common analysis tasks, and data exchange
To successfully accomplish the integrative analyses required in a consortium as diverse and compl with the AWG.

We have worked closely with the AWG and DCC to ensure that common analysis tasks are standardized. Such tasks include processing of RNA-seq datasets (short-read sequencing of mRNA), peak calling in ChIP-seq datasets (chromatin immunoprecipitation followed by deep sequencing), DNAme, and the
identification of sequence motifs and transcription factor (TF) bindin such frequently performed tasks, provide sound statistics for selecting among them, and work with the AWG to ensure uniformity in subsequent processing of each data type using the selected methods. The vast majority of ENCODE data is based on deep sequencing, a technology that only became widely practiced in the past few years. This presents potential biases and errors not yet completely understood, and thus we discuss plans for assessing the quality of ENCODE data.
Lastly, we will work closely with the DCC to facilitate data impo public datasets are available in a common repository and in uniform formats to ENCODE members. We will also ensure that all analysis results by ENCODE members are shared with the larger community, in accordance with the software guideline.

Below, we describe two examples: RNA-seq data for transcript annotation, and ChIP-seq data for TF binding and chromatin marks.

References for DNA methyaltion section

1. Hansen, K.D., Langmead, B. & Irizarry, R.A. BSmooth: from whole genome bisulfite sequencing reads to differentially methylated regions. *Genome*

research 42, e45 (2014).
8. Akalin, A. et al. methylKit: a comprehensive R package for the analysis of genome-wide DNA methylation profiles. *Genome biology* 13, R87 (2012).
9. (2014) .
10.

10. Marx, V. Genetics: profiling DNA methylation and beyond. Nature methods 13, 119-122 (2016).
11. Ziller, M.J., Hansen, K.D., Meissner, A. & Aryee, M.J. Coverage recommendations for methylation analysis by whole-genome b *Nature methods* 12, 230-232, 231 p following 232 (2015).

We will keep close communication with the DCC to ensure timely and consistent processing of raw data through a uniform pipeline. The output of the pipeline will be cleansed and normalized, ready for downstream analyses. We will assemble a subgroup of DAC analysts responsible for various aspects of uniform data processing and the data transform that is necessary prior to the uniform data processing. In particular, the subgroup will include analysts who have been part of
the uniform data processing during the current DAC and will appropriate DCC members to evaluate the status of uniform data processing pipelines. During the first three months of the project, all existing pipelines will be established and applied to all available datasets. This subgroup will be the point of contact with DCC on this issue. Whenever an analysis method has matured to
the stage of a pipeline, it will be turned over to this subgr

or We will work closely with the AWG and DCC to ensure that all analysis results, similar to primary data, are available in uniform formats from all groups, and additionally that all metadata are stored, including versions of programs used to generate the data, which pipeline version was used, and that all tools and
data processing methods remain available for the duration of representation, including for enhancers, promoters, transcripts, alternative splice forms, transcription start/end sites, genome segmentation etc. We will also make
sure that all analyses done in parallel in human, mouse, be responsible for ensuring reproducibility and consistency within the Consortium.

All data exchange will also be stored at the DCC servers, and all results of validated analyses will be made public upon validation, following the ENCODE common Data Release Policy. Care will be taken to anticipate the versioning of ENCODE data generated for all three organisms between different genome builds. As the
project progresses the data products generated earlier in the pr .
This will either be done via simple liftOver or via uniform reprocessing. We also anticipate data freezes (approximately every six months) where the collective set of all primary processed data products generated up until that stage by the entire Consortium are frozen for more detailed integrative downstream analyses.

We will also store at the DCC all public datasets which have been reformatted for ENCODE use by members of the DAC or AWG to minimize duplication of efforts, and ensure consistency between different groups. The DCC will also serve as our intermediate repository for all datasets coming from the epigenome project, the
1000 Genomes Project, TCGA, GTEx, Brainspan, GEO, SRA, FlyBase but they will be invaluable in preparing the datasets for integration, and preparing the integrative analysis for publication. Lastly, all data shared with the larger community will be shared through the DCC servers and browsers, and through FlyBase, WormBase, and general genome browsers (such as NCBI, ENSEMBL, and NCBI) whenever possible.

par One of the main roles of the DAC is to facilitate the analysis and writing of integrative Consortium papers, specifically the paper that describes the Encyclopedia of human and mouse. In addition, the DAC will assist with other Consortium reports such as data and analysis standards documents. The leadership of these papers and documents naturally springs from the leadership of the AWG and involves the interplay of many different scientists, and the DAC is at the service of this leadership by The DAC will performing various integrative analyses and providing a technological infrastructure.

eep In writing these papers the data from multiple techniques and approaches must be combined in a standardized fashion in order to maximize their utility The readers of the papers should also be able to see how large-scale genomic datasets have biological and medical utility. Thus, it is essential for the papers to
provide a clear linkage between the prose describing the re particular freeze to the literature has many scholarly advantages in terms of time stamping, attribution, and future citation

Aims 1-3 discussed the necessary calculations to enable these integrative analysis papers, and **..., keeppar**, keep here we focus on the infrastructure that the DAC will provide to enable these papers to be written. There are two aspects of this infrastructure: social and technological. In terms of social infrastructure, the DAC will organize and moderate phone calls as well as setting up and moderating meetings targeting particular analysis papers. For the conference calls and meetings we will handle creation of precise agendas and the recording of detailed minutes and action items.

wi,,keeppar There are a number of things to bear in mind regarding setting up a technological infrastructure for enabling collaborative papers. First of .
[in there is a vast and rapidly evolving industry in developing soc of main figures and tables as well as supplementary exhibits. Simply keeping track of all figures and supplements is a non-trivial task.

The DAC will facilitate the use of appropriate technology to help with this. Currently most of the genomics papers written by the ENCODE Consortium make use of mailing lists and conference calls for many of these interactions. To handle manuscript preparation addition they make use of resources such as Wikis, Google Docs, and reference managers such as Endnote, Bookends, and Papers. We will continue to use these types of infrastructures, and the DAC will provide expertise and resources in these areas for future Consortium publications. However we will also be aware of newly evolving tools that are currently being developed, including improved solutions for tracking references and figures (e.g., Mendeley and BibTeX). Also, online file sharing services such as Dropbox and SugarSync can be utilized for distribution of files and figures; we also intend to investigate the use of fully-fledged open-source content management systems such
as Drupal or Joomla. It is important to keep in mind that not be of as much use practically when employed by the various members of the Consortium, and thus we will have to keep track of their usefulness in terms of actual paper writing.

The writing of Consortium standards documents that focus on protocols and methodologies for data analyses and experimental procedures will
proceed in a similar way as the writing of integrative Consortium papers. One diffe sometimes to produce standardized datasets and standardized analyses that illustrate standard practices and provide a better third-party working-knowledge of the standard beyond that from individual production laboratories.

opar A third aspect of the DAC in writing large Consortium papers and standards documents is carefully connecting the underlying data to the prose. One can conceptualize a big genomics "roll out" (publishing a number of genomics papers commenting on a single underlying data freeze) as a hierarchical information structure, designed to present the Consortium's genomic data and results in an organized fashion. The "main" integrative paper sits at the top,
synthesizing everything broadly, which provides pointers to other analyses. Each of these individual papers, in turn, often refers to a huge amount of supplementary calculations and datasets. Some of these are in formal paper
supplements while others are on project Web sites. Moreover, t analysis products that summarize the data (e.g., peak call lists, transcript structures, and segmentations). At the bottom of the hierarchy is the actual underlying raw data (usually sequencing reads), stored in central repositories (such as the short-read archive). Given that the raw data files and, to some degree the analysis
summaries, are usually huge and unwieldy, it makes most s (assuming everything is linked together correctly). In the future one may see some machine readable, "structured" versions of the text of the paper (i.e., the
structured digital abstract and structured digital table^{118,12}

all There is an even more detailed micro-structure to the hierarchy: All of the data tables and figures in each paper rely on a considerable chain of small specific analysis results as well as programming scripts. These, in turn, connect to specific versions of the overall analysis summaries put out on the project website. One of the roles of genome analysts is to link these all together and make sure that it is clear which version of a particular analysis result goes with which version of the underlying data and how these in turn link with a specific paper figure. This can often be done through making available the small subsidiary
analysis files underlying each exhibit (such as networks co DAC and DCC. It will also push out larger analysis product datasets such as peak calls and segmentations regularly as part of data freezes and we will version these along with the underlying data from the production groups.

[[From old DAC4 grant (was in Aim 1 & moved by MG on 12-Mar)]]

We will create and analyze a meta-network composed of the TF regulatory network and protein-protein interactions integrated with the miRNA data. To integrate the miRNA data, the TargetScan software will be used to obtain the miRNA-TF edges in this network⁹⁸ by assessing complementarity of the miRNA seed region coupled with conservation information. This expanded, integrated network will be analysed using the tools and methodologies described below, allowing us to look for new types of motifs, regulatory patterns, and relationships that would likely remain undetected in individual analyses of the separate networks.

The networks will be analyzed using several methods to calculate key statistics. One such method is 'tYNA'⁹⁹, a web system developed to compare and mine multiple networks in order to identify cliques and motifs, as well as calculating statistics on a

network. Statistics such as 'eccentricity' and 'betweeness' can help explain the connectivity and behavior of nodes in a network¹⁰⁰. Eccentricity is defined as the maximum shortest path from a node to any other node in the network; this describes how a node interacts with all the other nodes it is connected to, i.e., a node with a small eccentricity is tightly connected to all nodes that it interacts with- including nodes to which it is not directly connected. Betweeness is defined as the number of shortest paths in the network that pass through a given node; this is a measure of a node's centrality and is related to how involved a node is the communications between all other nodes in a network. These and other statistics can help in the definition and understanding of a particular network.

Connectivity statistics, in particular the difference between out- (O) and in- (I) degree, elucidate the direction of information flow in the network and can reveal hierarchical organization. In previous work, we employed a simple simulated annealing procedure to arrange TFs into discrete levels that maximize the number of edges propagating down from higher to lower levels. To complement these discrete level assignments we defined a continuous parameter $h=(O-1)/(O+1)$, which can be interpreted as the height of a TF within the hierarchical structure. We plan to apply the same procedures to the transcriptional regulatory network in human, mouse, fly, and worm. Of particular interest is a comparison of the distribution of TFs between the different levels to determine, for example, the extent to which middle-level regulator nodes are conserved across different networks. Furthermore, it is important to evaluate the robustness of our results, as there exist several methods of constructing network hierarchies (e.g. breadth-first search) and we intend to assess the impact of various network construction methods on these results.

We have previously exploited the model of hierarchical organization by examining the degree of collaboration among different regulators¹⁰¹⁻¹⁰³. This is essentially the ratio of the number of genes co-regulated by two regulators (from the same or different levels) to the union of their target genes summed over all such pairs of regulators from the two levels^{102,103}. We found that in E. coli, yeast, and human the highest degree of collaboration is between regulators from the middle level, which is analogous to a corporate setting in which middle managers play an important organizational role. We plan to investigate the same arrangement using more comprehensive co-regulatory networks from human, mouse, worm, and fly. In addition to co-regulation we also studied the overlap between modules in terms of their position within the hierarchy. We defined a module as all accessible nodes downstream of a top regulator and investigated the overlap (share of regulators) between modules. We found that the modules in E. coli are more independent compared to those within the call-graph of the Linux kernel¹⁰⁴. We intend to examine the module-overlap in human, mouse, worm and fly, and other eukaryotes compared to our previous observations in E. coli. We speculate that these networks of more complex eukaryotes will be more similar to the Linux call-graph.

Building upon the expertise in dynamic Bayesian network (DBN) in the Noble lab in close collaboration with the Weng lab, we propose to develop computational methods to identify TF binding sites in a generalized way. We will focus in particular on the problem of predicting the results of a ChIP-seq assay for binding of a sequence-specific transcription factor in formulating the problem as follows. Other ENCODE data types

(e.g., chromatin accessibility measured by DNase-seq) can be easily incorporated into our computational framework. In a particular cell line or tissue, we are given several generic chromatin architecture datasets—e.g., DNase accessibility plus a variety of informative histone modification ChIP-seq assays—as well as the results of ChIP-seq experiments for a set of "training" TFs. We are then asked to predict what would happen if we were to run a ChIP-seq experiment for a given "test" TF, knowing only its binding affinity sequence motif, as determined from a ChIP-seq assay in another cell line.

This problem is akin to what is known in the field of speech recognition as "speaker adaptation." In that context, a system trained to produce a textual translation of a spoken utterance must learn to adapt to the peculiar characteristics of a new speaker. Similarly, our model will learn to adapt to the characteristics of a new TF, using methods developed in speech recognition. In particular, the model will predict the locations of in vivo binding events based upon features of the local chromatin architecture, while taking into account that some types of TF binding exhibit different local chromatin properties than others.

We will solve this problem using a combined classifier and DBN. The classifier (a support vector machine or a deep neural network) will learn to predict the binding of a given TF based on the observed local chromatin profile. We will train one such classifier for each TF in the training set. The scores produced by these classifiers will then be combined in the context of a DBN such as the one shown in Figure 6. In this model, MotifScore is an observed variable measuring how well the sequence starting at the current position matches the known motif of the target TF represented by its PSSM. The hidden variables state and Class indicate (respectively) whether a position is inside a binding site of the target TF and the identity of the training TF whose chromatin pattern is the closest match to those of the current position. In addition, the model contains one virtual evidence track for each of the *N* training TFs. Thus, *V^t ⁱ* is a positional virtual evidence variable that tells how well the chromatin pattern associated with the sequence starting at position *i* matches the patterns learned for the training TF *t*. Because every virtual evidence track corresponds to exactly one class value, we introduce a binary variable *I t ⁱ*, indicating the corresponding virtual evidence track of each class value. The conditional probability of this indicator variable, $Pr[I^t_i = 1|class_i = c]$, equals 1 only if $c = t$, and is 0 otherwise. As mentioned above, the virtual evidence, $Pr[\hat{V}^t_i = 1 | t^t_i]$, is produced by the TF-specific classifier. Finally, the observed binary variable missing is used as a switching parent of the virtual evidence nodes to handle positions where the chromatin profile contains missing data.

The accuracy of this predictive model can be validated in a prospective fashion within the context of ENCODE, because the Consortium is constantly producing new data. Accordingly, we will make predictions for experiments that are currently in the pipeline, and directly measure the accuracy of our predictions once the data become available. In addition to providing a valuable resource for TFs that have not yet been fully characterized experimentally and shedding light on the relationship between local chromatin architecture and TF binding, this project will enable us to prioritize future experiments. By investigating the dependence of prediction accuracy upon properties of the cell line, available local chromatin data, and properties of the TF itself, we will be able to predict which entries in the 2D experimental matrix can be easily imputed and which entries will likely provide the most value in training future imputation models.

Using protein domains to identify and evaluate orthologs: In addition to phylogenetic approaches, we will use protein domain annotations to help map orthologous proteins and evaluate ortholog assignments by other methods. We will use the Proteome Folding Pipeline¹⁰⁵ to sequentially analyze primary, secondary, and tertiary structures of protein sequences encoded globally in these four genomes. The analysis of potential 3D structures can allow us to recognize very distant homologs, as structural relationships can often be identified well into the "twilight zone" of sequence identity (as low as \sim 15-25%). Protein domains and structure will also provide testable functional hypotheses at the molecular level for directed experimental studies. We will use these results to help evaluate ortholog assignments, and compare the domain content of orthologous proteins, especially with regard to functional differences between the species.

A unique opportunity with ENCODE comes from the parallel experiments in human and mouse. We will study the relative role of pre- and post-transcriptional regulation in the two organisms, the interplay between orthologous transcription factors and orthologous chromatin marks, and the expression patterns, onset stages, targets, and target expression for orthologous factors and miRNAs. We will also study patterns of alternative splicing and alternative polyadenylation for orthologous genes in corresponding stages, especially with respect to how they affect miRNA targeting and functional protein domains. More generally, we will compare the transcription factor and miRNA inventory of the two species, the relative distributions of target gene counts for orthologous regulators, and similarly the relative distribution and diversity of regulators bound for orthologous gene targets. We will also study whether discovered modules of biologically related genes in **Aim 3.5** correspond to orthologous modules across species and for significantly conserved modules we will study the properties of gained and lost components. Using network properties discovered in **Aim 4.3** we will compare the two species in terms of determining if similar network motifs are discovered in the regulatory networks of the two species, and the types of feedback loops that are found in mixed TF/miRNA regulatory networks.

Old Aim 1 text on integrating ENCODE with other consortia [[ANS on 03/15/2016]]

The NIH Common Fund Epigenomics Roadmap Project (http://www.roadmapepigenomics.org/) and the International Human Epigenome Consortium
(http://www.ihec-epigenomes.org/) have generated rich maps of histone modifications, inc number of cell lines, maps of a few modifications in a large number of cell types, as well as maps of DNA methylation and DNA accessibility. As each of these data
types are widely used in the ENCODE Consortium, we will wor integrate relevant datasets into ENCODE pipelines for joint integrative analyses by the ENCODE AWG. For those cases in which we seek to integrate non-ENCODE datasets into our existing pipelines, we will ensure that such data meet the same quality standards as ENCODE datasets. To optimize the compatibility
with published papers by each of these consortia, we will use the reprocess the primary data according to the ENCODE uniform pipelines to ensure that data quality standards are met. $[2][3][4]$ Members of the DAC have been highly involved in the analysis of the Roadmap Epigenomics consortium datasets, and its continuation, the international human epigenome consortium (IHEC). In particular, we have jointly re-processed all raw datasets from ENCODE and the $\lceil 5 \rceil 6 \rceil 7 \rceil 8 \rceil$

***GTEx - Inter-relating ENCODE annotations with large-scale RNAseq & eQTLs [[Roderic, Manolis, normalize, harmonize eQTLs]]

Other sources of complementary, large-scale human data include the NIH GTEx (Genotype-Tissue Expression) Project (http://genome.gov/gtex), the NIMH Brainspan Project (http://brainspan.org), and the NCI Cancer Genome Atlas (TCGA) Project (http://cancergenome.nih.gov). Over 1,200 data samples from primary tissues have already been collected and analyzed during the initial stages of the GTEx project. We propose combining the large amount of population-specific
lymphoblastoid genotype and mRNA expression data in ENCODE with In addition, compilation and comparison of DNA methylation, mRNA/miRNA expression, as well as genotype data from ENCODE, GTEx, and Brainspan, will
permit a robust analysis of the expression landscape of the human brain and scale, high-quality datasets

***PsychENCODE/BrainSpan [[Gerstein, Weng, normalize, look consistency in pipelines, connect w eQTLs]]

We will compare parameters like thresholds for calling peaks in ChIP-seq data, look at discrepancies between the two projects and calibrate parameters to reduce biases due to cross-project analyses. In addition to comparing the parameters in the uniform processing pipelines, we will also directly compare the annotated genomic regions or transcripts called by these pipelines. For example, we will identify the brain cell types studied by ENCODE and other consortia, match them
with the most appropriate datasets in psychENCODE, and investig replicates, and focus on the regions and transcripts deemed most significant by either or both pipelines. If we identify major differences, we will investigate whether they are due to the underlying raw data, or the differences in the pipelines.

***exRNA [[Gerstein, shorten, different types]]

Moreover, Gerstein lab has considerable expertise in developing standardized pipelines and quality control metrics for RNA-seq and evaluating them in many
consortia including the Extracellular RNA Communication Consortium exRNA-seq data for the Extracellular RNA Communication Consortium (ERCC). The Gerstein Lab is in charge of the DIAC of the exRNA consortium to develop
the standardized RNA-seq pipelines for the analysis of exRNAs.

***1000 Genomes & Germline Variants [[Gerstein]]

We aim to integrate different non-coding annotations with the variants identified by the 1000 Genomes Consortium. In this way, the non-coding annotation of each variant will be available to all users of the 1000 Genomes data and should serve as a valuable resource for the genetics community to identify the causal variant in
GWAS. It will also provide easy access to downstream anal different annotation classes. The integration of ENCODE data with 1000 Genomes variants (SNPs, small insertions and deletions, and large structural variants) will be provided in the annotated Variant Call Format (VCF; <u>http://www.1000genomes.org/node/101</u>) These VCF files will contain the annotation of each genomic
variant, including presence in non-coding RNA, TF peaks, TF motifs, identified with a distinct tag in the VCF files.

***TCGA/ICGC/PCAWG - Somatic Variants & Cancer Functional Genomics Data [[Shirley, Gerstein, somatic variants & also harmonizing RNA-seq]]

Finally, the integration of the large volume of ENCODE cancer data (from both primary tissue samples and immortalized cell lines) with over 500 clinical samples in
TGCA will enable analyses of somatic mutations, mRNA/miRNA

***4D Nucleome Consortium [9] - [[Noble, More elaborate chromatin annotations]]

Recently, Dr. Noble and and Dr. Jay Shendure, in collaboration with five other UW investigators, were awarded a U54 center grant as part of the NIH 4D
Nucleome Consortium. With Bing Ren, Dr. Noble is co-chairing the steeri

Consortium. Dr. Noble is thus in an excellent position to ensure coordination between the ENCODE and 4D Nucleome consortia.
We have already developed one computational method that will facilitate integration between ENCODE a principled method for making use of Hi-C data during the semi-automated annotation of the genome 41 (); 64 (). GBR expresses a pairwise prior that encourages certain pairs of genomic loci to receive the same label in a genome annotation. We used GBR to exploit Hi-C data during genome annotation by encouraging
positions that are close in 3D to occupy the same type of domain. Usi thereby revealing the relationships among known domain types. Through this model, we identified clusters of tightly regulated genes expressed in only a small
number of cell types, which we term "specific expression domains between cell types even when domain activity changes. During the next phase of the ENCODE project, we will deploy GBR in Segway, thereby making use of Hi-C data being generated both within ENCODE and by the 4D Nucleome Consortium.
We will also explore the use of Hi-C and other ENCODE data types to assist in 3D structural inference. One particularly valuable, orthogonal type o

that the 4D Nucleome Consortium will be generating is microscopy data. For example, oligopainting data can be used to visualize different types of topologically
associated domains 65 (). We will use such data in combinatio (). Accordingly, a series of hyperparameters corresponding to domains of different sizes will adjust the Poisson distribution in the Pastis model, or the Poisson
rates might be sampled from a prior distribution derived fro

which empirical evidence based on Hi-C suggests tend to bind to regions on the outside of the 3D structure 9 (). $\lceil 10 \rceil \lceil 1 \rceil$

2.XXX. Data integration for defining protein-coding and non-coding genes and transcripts. $[12]$

To characterize coding and non-coding transcripts, we will integrate RNA-seq data, promoter-associated chromatin marks, transcription elongation-associated chromatin marks, and comparative genomics of related species.

Transcriptional evidence: Several types of data generated by ENCODE provide transcriptional evidence⁵⁶: RNA-seq can be used to derive the structure and level of transcripts, CAGE determines the precise positions of the 5' ends of transcripts, and RNA-PET (also called diTAGs) provides connectivity for the 5' and 3' ends of transcripts. Moreover, ENCODE has generated transcript data with high-density (5 bp) tiling DNA microarrays for some cell lines.

Chromatin evidence: We have found that distinct combinations of chromatin marks and chromatin accessibility are associated with promoter regions, transcribed regions, and transcription termination regions. Surprisingly, internal exon-intron boundaries are also associated with distinct chromatin marks and nucleosome positioning biases⁵⁷, suggesting that these can be used as an additional line of evidence in defining transcript boundaries, especially with respect to low-expression genes for which the transcriptional evidence may be weaker. We have recently used such marks to discover more than a thousand novel long
intergenic non-coding RNAs (lincRNAs) in mouse⁵⁸ and more recently in human²⁴.

Comparative evidence: The Kellis lab identified evolutionary signatures that are uniquely associated with each class of functional elements⁵⁹, with protein-coding genes showing distinct patterns of codon substitution frequencies and reading-frame conservation, non-coding RNAs showing compensatory changes and silent GU-involving substitutions, miRNAs showing a distinct conservation profile (high conservation in the star and mature arm and lower conservation in loop and flanking regions), and other structural conservation properties. We used these signatures to reveal at least 30 non-coding genes in the fly genome using modENCODE transcript data and comparative genomics of 12 Drosophila species⁶⁰. We will apply a similar approach to human and mouse ENCODE data.

Combinations of features: We will combine these transcriptional, chromatin, and comparative features to distinguish different classes of genes in a machine learning framework. We will use Support Vector

Machines to classify each transcript into coding or non-coding. We will also apply a previously developed Conditional Random Field (CRF) framework to predict coding and non-coding exons and transcripts from the combined evidence. CRFs are graphical probabilistic models similar to Hidden Markov Models (HMMs) but they allow much richer feature sets due to their discriminative training nature. Lastly, we will associate noncoding RNAs with precursors of miRNAs, piRNAs, and other classes of small RNAs using short-RNA sequencing results.

Identification of non-coding RNA genes: We will utilize an integrative machine learning approach for identifying novel non-coding RNA ($ncRNA$) genes¹⁷. The method is based on support vector classification to classify non-coding RNAs from other elements like coding sequences and UTRs. For each non-coding RNA, a set of features are computed which are then used for training. These features comprise the quantities that are chosen to maximize the discriminatory power of the machine-learning algorithm. For example, high short RNA-seq expression levels, high secondary structure stability and conservation, medium nucleotide conservation, and low amino acid conservation are the expected characteristics for the non-coding RNAs. The machine learning algorithm enables combining these features for prediction of the new ncRNAs in a formal manner. The known non-coding RNAs are utilized as the training set for the method. We will then apply the method on the remaining unannotated parts of the genome to discover novel non-coding RNA genes.

2.XXX Correlating gene expression with TF binding and histone modifications: Transcriptome monitoring by RNA-seq can provide accurate genome-wide estimates of the steady-state abundance of transcripts. Such estimates are essential to fully understand the pathways involved in RNA biogenesis. A number of genetic and epigenetic factors cooperate to determine the abundance of a specific RNA species in a particular cellular compartment: 1. signals in genomic DNA and in intermediate RNA molecules, e.g., TF binding sites, splicing regulatory sites, and polyadenylation signals; 2. the structure and status of chromatin; and 3. the abundance and concentration of the regulatory molecules—including both proteins and RNAs themselves. The relative contribution of each of these factors and their mode of cooperation, are largely unknown. The goal of the ENCODE Project is to simultaneously monitor many of these factors across multiple cell conditions and types.

Given the gene expression data from RNA-seq and the TF binding or histone modification data from ChIPseq experiments, the Gerstein and Weng labs have investigated their relationship in a quantitative fashion^{5,61}. We have previously constructed TF models and histone modification models in different species from yeast to human^{18,62,63}. Our results indicate that both TF binding and histone modifications are predictive of gene expression levels in a position dependent manner, and either account for at least 50% of gene expression level variation. The histone modification model accurately predicts gene expression in a wide chromatin region from the promoter to the transcribed regions, whereas the TF model achieves high accuracy only in a narrow chromatin region around transcription start sites (TSSs) of genes (Figure 4). Our study also indicates that TF and histone modifications are highly coordinated during transcriptional regulation and a combination of TF and histone modification signals does not further improve prediction accuracy relative to using each alone.

Based on the CpG content, promoters of genes can be divided into high CpG (HCP) and low CpG (LCP). Interestingly, we find that expression levels of HCPs are easier to predict than those of LCPs⁵. More detailed analysis indicates that the relative importance of TFs and histone modifications in the models are different between the two promoter categories. These results suggest different regulatory mechanisms between HCPs and LCPs. The prediction accuracy of TF and histone modification models to some extent reflects the quality of the expression data. For example, the models achieve significantly higher accuracy for expression measured by RNA-seq than by microarray. In addition, the models can also be used to predict the expression levels of non-coding RNAs (miRNAs) with fairly high accuracy. In the future, we suggest using the TF and histone modification models as a benchmark to understand transcription regulation.

Predicting alternative splicing using chromatin modifications and TF binding. We propose to investigate how inclusion levels of alternative exons covariate with histone modifications and TF binding, which will help us understand how these factors cooperate to modulate the specific abundance of RNA splice variants in the cell. Sophisticated probabilistic models have been recently developed to successfully predict tissue specific exonic inclusion⁶⁴. However, the splicing code delineated in such a way includes hundreds of variables, many of which are concomitant but unlikely to be mechanistically involved in splicing. Within the current phase of ENCODE the Guigo lab has used statistical models to explore the relationship between levels of histone modifications and inclusion of exons. We found that, even when controlled for gene expression, some histone marks (e.g., H3K9ac and H3K36me3) are consistently significant (albeit weak) predictors of exon inclusion, and we built a predictive model of exon inclusion by combining the signals of these marks^{25,28} (Figure 5). By computing a measure of splicing completion on RNA-seq datasets obtained in different sub-cellular compartments, we found strong evidence that splicing in the human genome occurs predominantly during transcription²⁹, providing a molecular justification to the increasing evidence

connecting chromatin with splicing⁶⁵. We propose to further develop and apply statistical methods to the data obtained through the ENCODE Project, as well as to other publicly available data, to identify novel genetic and epigenetic factors involved in RNA processing, splicing in particular. We propose to:

1. Identify and characterize histone modifications that play a role in the regulation of alternative splicing, using correlation and modeling analysis.

2. Apply methods used to investigate the distribution of TF binding sites in promoter regions to investigate their distribution in exons and exon-intron boundaries. We will further correlate exon skipping events, as measured by RNA-seq, with differential binding of TFs.

3. Identify novel regulators of splicing by searching for co-variation between the levels of exon inclusion (or alternative splicing events in general) and gene expression. This approach will uncover protein coding genes not yet known to play a role in splicing regulation, and more interestingly, lncRNAs that may act as splicing regulators. The RNA expression levels of protein coding genes are only a proxy for protein expression—the latter is the effector of the biological function. In contrast, expression levels of lncRNAs are almost the actual physiological levels. Inferences based on co-variation between exon inclusion and abundances of lncRNAs are therefore more likely to be biologically meaningful.

4. We will investigate the relationship between RNA expression levels, protein expression levels, and protein binding activity—both to DNA and RNA—for transcription and splicing regulators, and determine how they relate to cellular abundance of the regulated RNAs.

2.XXX Associate TF/miRNA with their targets:

Given a high-quality annotation of enhancers, promoters, insulators, protein-coding genes (including all transcription factors, TFs), microRNAs, and other non-coding RNAs, we will work to piece together regulatory networks based on condition-specific TF binding, conserved TF motif instances in active promoter and enhancer regions, and conserved miRNA motif instances in 3'UTRs. We previously showed that comparative genomics of the 12 Drosophila genomes enables the high-accuracy definition of regulator targets, and that combining comparative genomics with condition-specific TF binding led to a further increase in signal⁶⁷.

Binding vs. regulation: We will use condition-specific changes in gene expression levels of TFs, miRNAs, and their targets to distinguish 'biochemical' binding from 'biological' transcriptional regulation. We previously showed that bound motifs associated with expression changes are under stronger selective pressure across related species, and show stronger functional enrichments⁶⁷. This suggests that we can use positive or negative expression changes to further annotate our inferred transcriptional networks with activation, repression, or simply binding edges, when no effect is detectable. We have further characterized the chromatin and sequence context of each of these three classes of edges, to search for predictive features of each class that could lead to new insights on the logic of gene regulation⁶⁸.

2.XXX miRNA regulation: A complete view of mixed TF/miRNA pre- and post-transcriptional networks requires accurate promoter and enhancer annotation for miRNA precursors, and accurate tissue- and stagespecific 3'UTRs for all miRNA target genes. Kellis led the fly modENCODE integrative paper and generated TF/miRNA regulatory networks⁶⁰ (Figure 7) and we will perform similar analysis on human and mouse ENCODE data. We will use chromatin marks to annotate miRNA promoters based on genomic proximity and tissue-correlated activity. We will use the longest 3'UTR from updated gene models combined with multispecies sequence alignments based on the most up-to-date genome alignments with all sequenced species to identify evolutionarily conserved 3'UTR target sites. We will search for and re-evaluate previouslydiscovered 3'UTR motifs that were not associated with miRNAs to determine whether we can now identify putative trans-acting agents that may mediate regulation through these sites. We will also evaluate the potential for other non-coding genes to serve as targets for miRNA regulation. Lastly, we will study the effect of alternative polyadenylation sites on miRNA regulatory networks. We have identified many such sites within protein-coding transcripts resulting in loss of key functional miRNA binding sites, which may play key roles in altering regulatory relationships during development and proliferation. We will look for anticorrelations between miR NAs and their predicted targets, and assess whether transcripts with short vs. long 3'UTR isoforms which exclude or include conserved miRNA binding sites, differ in expression in the presence of cognate miRNAs. This may have major implications for human gene regulation as well, as the Burge and Sharp labs reported that proliferating cells, and by extension cancer cells, preferentially shift towards shorter transcript isoforms that escape miRNA regulation 70