

## Detection of Alternative Splicing Events Using Machine Learning

G. Rätsch<sup>1</sup>, S. Sonnenburg<sup>2</sup>, B. Schölkopf<sup>3</sup>, R. Bohnert<sup>1</sup>, C.S. Ong<sup>1,3</sup> and H. Shin<sup>1</sup>

- <sup>1</sup> Friedrich Miescher Laboratory, Tübingen, Germany
- <sup>2</sup> Fraunhofer FIRST, Berlin, Germany
- <sup>3</sup> Max Planck Institute for Biol. Cybernetics, Tübingen, Germany

http://www.fml.tuebingen.mpg.de/raetsch

# **Background & Motivation**

### From DNA to protein

- genes organized in exons & introns
- <u>transcribe</u> DNA to pre-mRNA
- Splicing removes introns  $\Rightarrow$  mRNA
- mRNA is translated into protein

### Alternative Splicing (AS)

- can produce several mRNA transcript per gene (sometimes leading to >> 100 slightly different proteins)
- is highly regulated
- greatly increases the proteome diversity in eukaryotes

### $\geq$ 70% of human genes are alternatively spliced!







# Motivation



#### Alternative Splicing (AS)

- Sector can produce several mRNA transcript per gene (sometimes leading to  $\gg$  100 slightly different proteins)
- is highly regulated
- greatly increases the proteome diversity in eukaryotes

 $\geq$ 70% of human genes are alternatively spliced!

# Motivation



### Alternative Splicing (AS)

- Sector can produce several mRNA transcript per gene (sometimes leading to  $\gg$  100 slightly different proteins)
- is highly regulated
- greatly increases the proteome diversity in eukaryotes

 $\geq$ 70% of human genes are alternatively spliced!

Methods for identifying alternative splicing

- usually need many EST sequences or
- exploit conservation between several organisms

Novel AS prediction method only using the pre-mRNA





#### Splice sites are



the exon/intron boundaries





#### Splice sites are

- the exon/intron boundaries
- recognized by five snRNAs assembled in snRNPs





#### Splice sites are

- the exon/intron boundaries
- recognized by five snRNAs assembled in snRNPs







#### Splice sites are

- the exon/intron boundaries
- recognized by five snRNAs assembled in snRNPs
- flanked by regulatory elements

#### **Spliceosomal Proteins**

- interact with snRNPs and mRNA
- regulate recognition of splice sites





#### Splice sites are

- the exon/intron boundaries
- recognized by five snRNAs assembled in snRNPs
- flanked by regulatory elements

#### **Spliceosomal Proteins**

- interact with snRNPs and mRNA
- regulate recognition of splice sites
- can lead to alternative transcripts

One gene may correspond to several transcripts/proteins

# Forms of Alternative Splicing





#### Idea: Use Machine Learning to

- analyze sequences near splice sites
- understand differences between alternative and constitutive splicing
- exploit and identify regulative splicing elements
- predict yet unknown alternative splicing events

## **Forms of Alternative Splicing**





# **Alternatively Spliced Exons**







#### Idea: Use Machine Learning to

- understand differences between alternative and constitutive splicing
- exploit and identify regulative elements
- predict unknown alternative splicing events

### Previous work:

- Analysis of conserved alternatively spliced exons
  - $\Rightarrow$  Sorek et al.. Yeo et al. and others
  - consider conserved alternative spliced exons (ACE)
  - exploit that ACE and flanking introns are more conserved between mouse and human
- Problem: only works for conserved exons
- Difference to our approach:
- we only use features derived from the pre-mRNA

# **Prediction of Alt. Spliced Exons**



- Two different Tasks:
  - Exon is known
  - Can it be skipped?



- Intron is known
- Does it contain an exon?



### Two different Tasks:

- Exon is known
- Can it be skipped?

- Intron is known
- Does it contain an exon?



- $\Rightarrow$  Use Support Vector Machines (SVMs) on
  - $\blacksquare$  sequences A & B ( $\pm$  100nt of splice sites)
  - exon & intron lengths



# **Prediction of Alt. Spliced Exons**



- Two different Tasks:
  - Exon is known
  - Can it be skipped?





- Problem: We do not know yet the exon boundaries!
  - Solution: Consider all possible exons within the intron.

# **Prediction of Alt. Spliced Exons**



### Two different Tasks:

- Exon is known
- Scan it be skipped?





- Problem: We do not know yet the exon boundaries!
  - Solution: Consider all possible exons within the intron.
  - Classify true exons vs. wrong exons
- $\Rightarrow$  Use SVM-like algorithm using the
  - $\blacksquare$  sequences A & B ( $\pm$  100nt of splice sites)
  - exon & intron lengths and
  - splice site scores (SVM based)

# **Generating Decoys on the Fly**



- **9** find function  $f(\mathbf{e})$  that scores exons  $\mathbf{e}$ :

- Training examples:
  - Introns that contain exon  $\mathbf{e}_i^+$  and many decoys  $\mathbf{e}_{i,j}^-$

 $f(\mathbf{e}_i^+) \ge 1 - \xi_i$  $f(\mathbf{e}_{i,j}^-) \le -1 + \xi_i$ 

• Introns without exons with many decoys  $\mathbf{e}_{i,j}^-$ 

$$f(\mathbf{e}_{i,j}^{-}) \le -1 + \xi_i$$

- minimize  $\sum_i \xi_i + C\mathbf{P}(f)$  (Linear Program)
- Too many decoys! Use Column Generation technique:
  - iteratively include decoys with violated constraints
  - fast & guaranteed convergence

## A novel kernel for sequences



#### Weighted Degree Kernel (Sonnenburg & Rätsch, 2002)

 $k(s_1,s_2) = w_7 + w_1 + w_2 + w_2 + w_3$ 

- finds motifs at specific positions
- fails if motif positions vary

new kernel shifts sequences against each other:



improved recognition of motifs at nearby positionsadditionally: information about exon & intron lengths

# Method for Interpreting SVMs



### Weighted Degree kernel: linear comb. of LD kernels

$$k(\mathbf{x}, \mathbf{x}') = \sum_{d=1}^{D} \sum_{l=1}^{L-d+1} \gamma_{l,d} \mathbf{I}(\mathbf{u}_{l,d}(\mathbf{x}) = \mathbf{u}_{l,d}(\mathbf{x}'))$$

- Designed a new method for optimizing the coefficients  $\gamma \Rightarrow$  Multiple Kernel Learning
  - $\Rightarrow$  Wrapper algorithm based on column-generation
- For instance result for classifying splice sites:



## **Computational Results**



- 487 alternatively and 2531 constitutively spliced exons ...derived from EST data base (*C. elegans*)
- model selection and testing via 5-fold cross-validation



# **Understanding the Classifier**



- What does the algorithm use for discrimination?
- Apply a Multiple Kernel Learning algorithm
  - $\Rightarrow$  optimizes a combination of kernels (Sonnenburg, Rätsch & Schäfer, 2005)
- Which positions are important?



# **Understanding the Classifier**



- What does the algorithm use for discrimination?
- Apply a Multiple Kernel Learning algorithm
  - $\Rightarrow$  optimizes a combination of kernels (Sonnenburg, Rätsch & Schäfer, 2005)



	Which	motifs	are	important?
--	-------	--------	-----	------------

	Hexamer	E-value
-	TTTAAA	1.8e-12
	AATTTT	2.2e-10
	ATTTTA	2.9e-09
	CAGCAG	1.2e-08
	TAATT	8.3e-08
	TTCCCC	2.1e-07
	TTTTTT	5.2e-07
	ATATAT	7.8e-07
	ATTTAA	1.3e-06
	TAAAAA	1.5e-06
	GCTAGC	5.1e-06
	AGGCGG	5.9e-06

Red: 5-mers found in Yeo et al., 2005, for human (p < 1.2%)

## Wetlab Results



- 21,000 exons and 28,000 introns (single EST confirmed)
- 25 random exons & introns from 1-2% top ranks
- RT-PCR with primers in flanking exons —
- Gel separation & direct sequencing for verification



## Conclusions



Based on wetlab experiments and accuracy estimates: (in our test set)

- I  $\approx$  0.25% of AS exons are yet completely unknown
- $\checkmark$   $\approx$  280 AS spliced exons (total)
  - 13 confirmed by RT-PCR
  - additional  $\approx$  80 AS exons can be found with less than 200 additional RT-PCRs

Genome-wide: around 4x more (some are known already)

Predictions for C. elegans are available at
http://www.fml.tuebingen.mpg.de/raetsch/projects/RASE

# **Empirical Inference Challenges**





- Predicting the simple cases is not enough
- $\Rightarrow$  need to predict the gene structure
- Difficult learning setting:
  - Input: DNA sequence
  - Output: Splicegraph (vertices & edges unknown)

## Summary



- Solved two tasks using SVM-like algorithms:
  - Classification of known exons (AS vs. CS)
  - Finding yet unknown AS exons
- Accurate predictions of AS exons is possible ...
  - even without assuming conservation
- Wetlab experiments support computational results
- A few more experiments will reveal many more AS exons
- Future work
  - human and other organisms
  - other alternative splicing variants ...
  - ... in combination with *ab initio* gene-finding

# **Thanks for your attention!**



Details, Data sets & Predictions:

http://www.fml.tuebingen.mpg.de/raetsch/projects/ RASE

#### Acknowledgments:

- Uwe Ohler, Gene Yeo & Klaus R. Müller for discussions
- Sommer Lab for providing C. elegans mRNA

Postdoc & PhD student positions/scholarships available

Please contact:

Gunnar Rätsch (Gunnar.Raetsch@tuebingen.mpg.de) Friedrich Miescher Laboratory, Tübingen, Germany http://www.fml.tuebingen.mpg.de/raetsch/jobs

## Links



### Homepage

http://www.fml.tuebingen.mpg.de/~raetsch

- Details, Data sets & Predictions for alt. splicing http://www.fml.tuebingen.mpg.de/raetsch/projects/ RASE
- Work on Splice site detection: http://www.fml.tuebingen.mpg.de/raetsch/projects/ AnuSplice
- Work on Large Scale Multiple Kernel Learning http://www.fml.tuebingen.mpg.de/raetsch/projects/ mkl\_splice

Workshop on "New Problems and Methods in Computational Biology" http://www.fml.tuebingen.mpg.de/nipscompbio