

# New Methods for Splice Site Recognition

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# ROADMAP: CLASSIFICATION OF SPLICE SITES



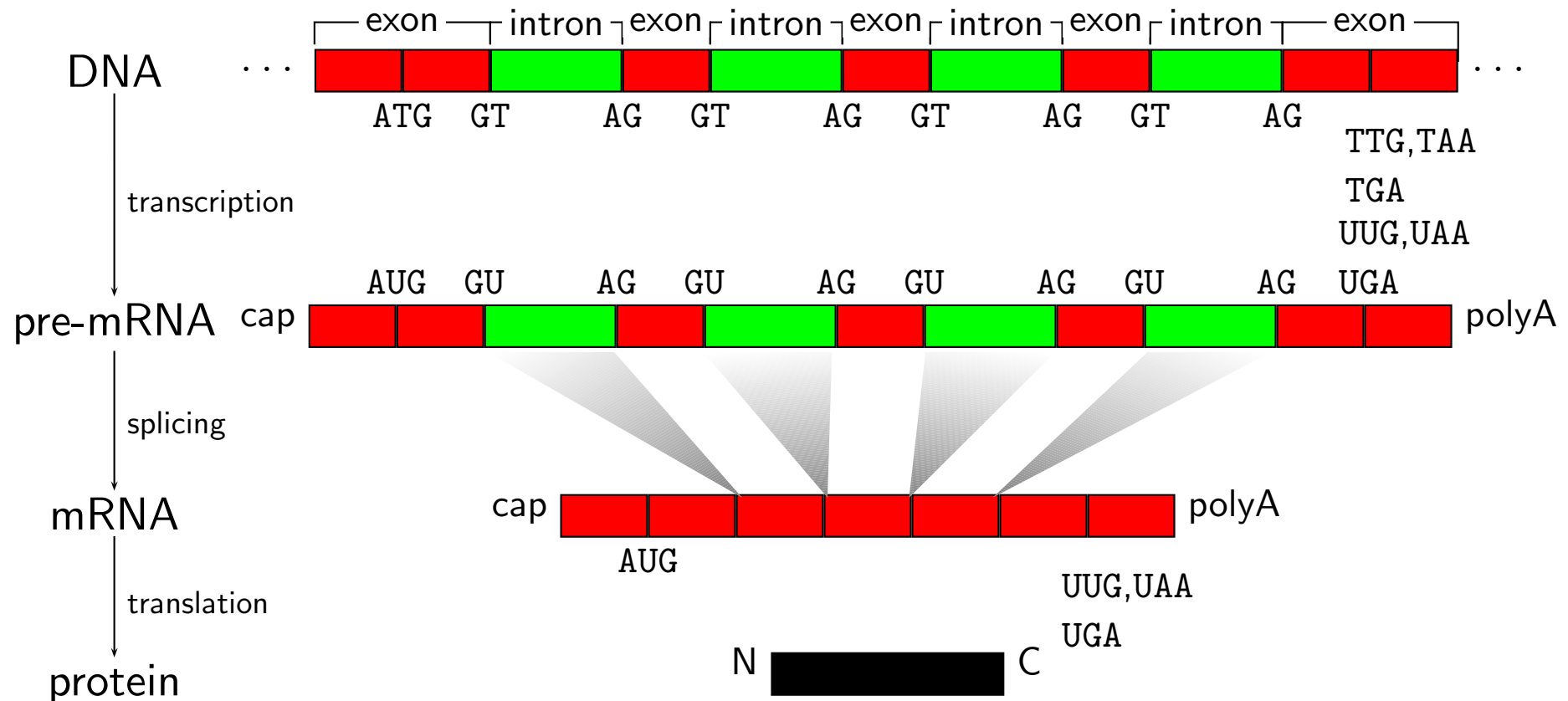
- Biological Introduction to Splice Sites
- Prior Knowledge for Splicing and ML
  1. engineering
  2. generative
- Benchmarking on the IPData dataset (human)
- Experiments on the *C. elegans* genome
- Conclusion

**Aim: Improve the splicing module in a gene finder**

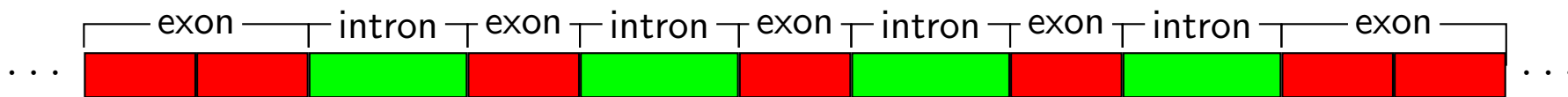
# BIOLOGICAL BACKGROUND

**Splice sites** are locations on DNA at boundaries of

- **exons** (which code for proteins)
- **introns** (which do not)



## FACTS ABOUT SPLICE SITES



- **Exons** are short (100 – 200 bp); **Introns** can be very long (> 1 kbp)
- The splicing process takes place in the cell's *nucleus*.
- The apparatus for splicing ( "**Spliceosome**" ) is not tissue specific
- Splicing mechanisms are very similar for all higher organism
- Experiments show that any 5' site could be connected to any 3' site

**The splicing mechanism uses *local* information**

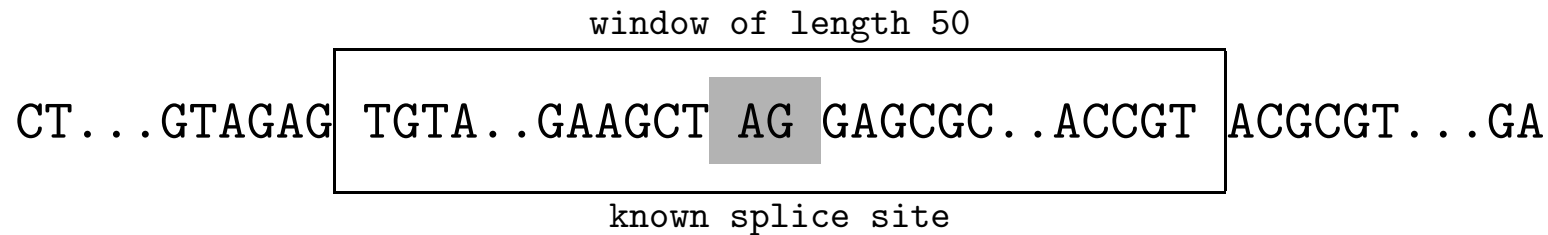
## WHY IS SPLICE SITE DETECTION IMPORTANT?

- allows to *accurately* predict mRNA and thus proteins from DNA
  - ⇒ important step in analyzing the genome
- splice sites can be detected with high accuracy
  - ⇒ important and accurate 'marker' to find locations of genes

**Conventional: alignment to data base entries**

**Aim: Improve the Splicing module with ML**

## TWO-CLASS CLASSIFICATION PROBLEM



- only considered canonical splice sites (consensus AG,GT, 98%)
- **true splice sites**: fixed window around splice site
- **decoys**: created by sliding the window  $\pm 25$  bases

```

AAACAAATAAGTAACTAATCTTTAGGAAGAACGTTTCAACCATTTTGAG
AAGATTAAAAAAAACAAATTTTTCATTACAGATATAATAATCTAATT
CACTCCCAAATCAACGATATTTTAGTTCACTAACACATCCGTCTGTGCC
TTAATTTCACTTCCACATACTTCCAGATCATCAATCTCCAAAACCAACAC
TTGTTTTAATATTCAATTTTTTACAGTAAGTTGCCAATTCAATGTTCCAC
TACCTAATTATGAAATTAATAATTCAGTGTGCTGATGGAAACGGAGAAGTC
  
```

Download at <http://mlg.anu.edu.au/~raetsch/splice>

# SUPPORT VECTOR MACHINES

- sequences  $\mathbf{x}_i \in \mathbb{X}$  ( $i = 1, \dots, \ell$ ) with respective labels  $y_i$
- SVM classifier (essentially perceptron in kernel feature space):

$$f(\mathbf{x}) = \text{sign} \left( \sum_{i=1}^{\ell} y_i \alpha_i \mathbf{k}(\mathbf{x}, \mathbf{x}_i) + b \right)$$

- find parameters  $\alpha$  by solving quadratic optimization problem:

$$\max_{\alpha} \sum_{i=1}^{\ell} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{\ell} \alpha_i \alpha_j y_i y_j \mathbf{k}(\mathbf{x}_i, \mathbf{x}_j)$$

subject to  $\alpha_i \in [0, C]$ ,  $i = 1, \dots, \ell$ ,  $\sum_{i=1}^{\ell} \alpha_i y_i = 0$ .

## Solution has no local minima

# ENGINEERING KERNELS I

## Polynomial Kernel of degree $d$ :

$$k_{\text{POLY}}(\mathbf{x}, \mathbf{x}') = \left( \sum_{p=1}^l l_p(\mathbf{x}, \mathbf{x}') \right)^d$$

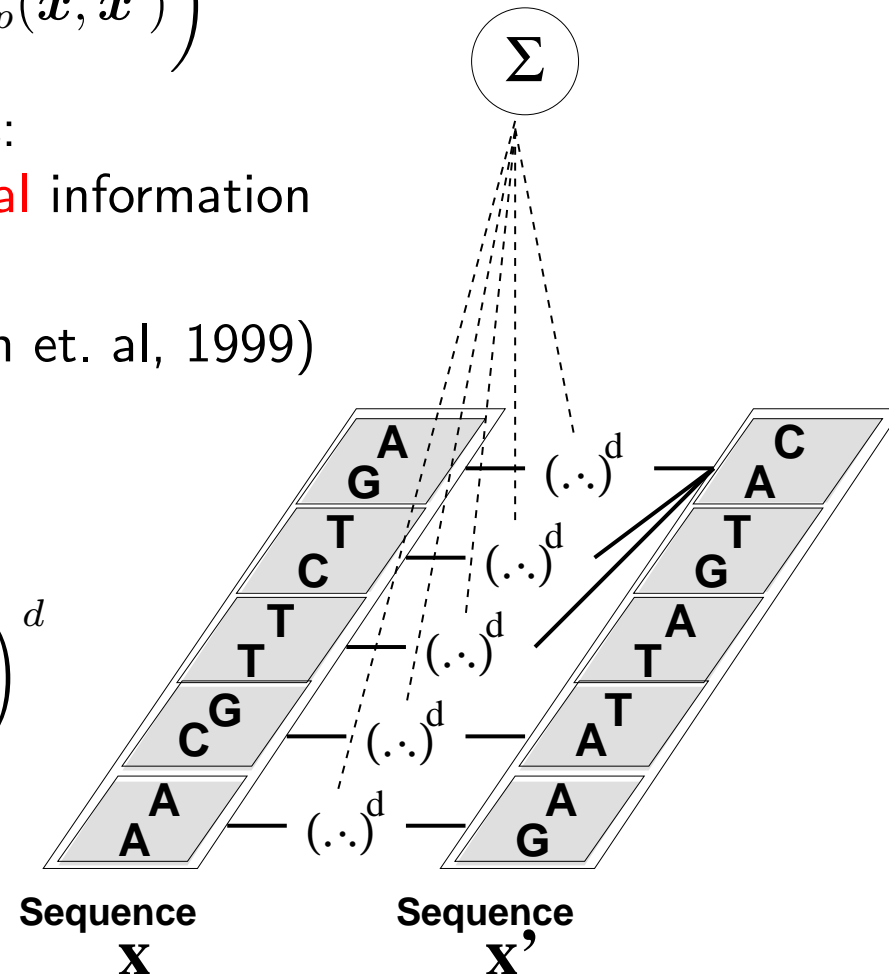
⇒ Computes all  $d$ -th order monomials:  
uses **global** information

## Locality Improved Kernel (Zien et. al, 1999)

$$k_{\text{LI}}(\mathbf{x}, \mathbf{x}') = \sum_{p=1}^N \text{win}_p(\mathbf{x}, \mathbf{x}')$$

$$\text{win}_p(\mathbf{x}, \mathbf{x}') = \left( \sum_{j=-l}^{+l} p_j l_{p+j}(\mathbf{x}, \mathbf{x}') \right)^d$$

$$l_i(\mathbf{x}, \mathbf{x}') = \begin{cases} 1, & x_i = x'_i \\ 0, & \text{otherwise} \end{cases}$$

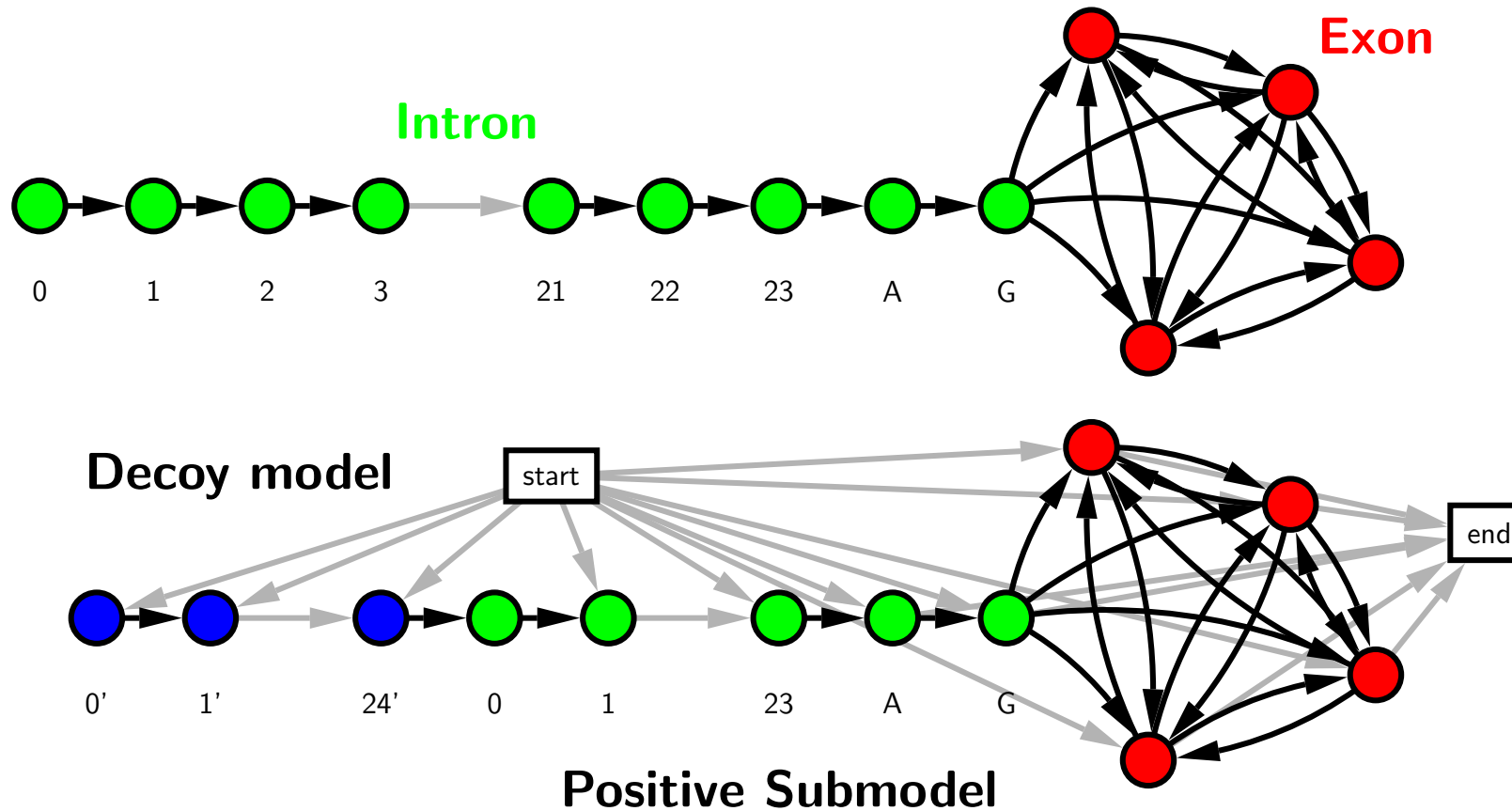


**Idea:** Spliceosome uses only **local** information → we need **local** classifiers



# GENERATIVE MODELS

Use generative model, e.g. design a HMM



(top) positive acceptor model, (bottom) negative acceptor model

## ENGINEERING KERNELS II

- Kernels from generative models
  - compare objects using a generative model  $\Pr(\mathbf{x}|\Theta)$
  - exploit probabilistic model for **discriminative** training
- Fisher Kernel (Jaakkola and Haussler, 1998)

$$\mathbf{k}_{\text{FK}}(\mathbf{x}, \mathbf{x}') = \mathbf{s}(\mathbf{x}, \hat{\boldsymbol{\theta}})^\top \mathbf{Z}^{-1}(\hat{\boldsymbol{\theta}}) \mathbf{s}(\mathbf{x}', \hat{\boldsymbol{\theta}})$$

$$\mathbf{s}(\mathbf{x}, \hat{\boldsymbol{\theta}}) = \nabla_{\boldsymbol{\theta}} \log \Pr(\mathbf{x}|\hat{\boldsymbol{\theta}}) \quad \text{Fisher score vector}$$

$$\mathbf{Z}(\hat{\boldsymbol{\theta}}) = \mathbb{E}_{\mathbf{x}} \left[ \mathbf{s}(\mathbf{x}, \hat{\boldsymbol{\theta}}) \mathbf{s}(\mathbf{x}, \hat{\boldsymbol{\theta}})^\top \mid \hat{\boldsymbol{\theta}} \right] \quad \text{Fisher information matrix}$$

- TOP Kernel (Tsuda et. al, 2002)

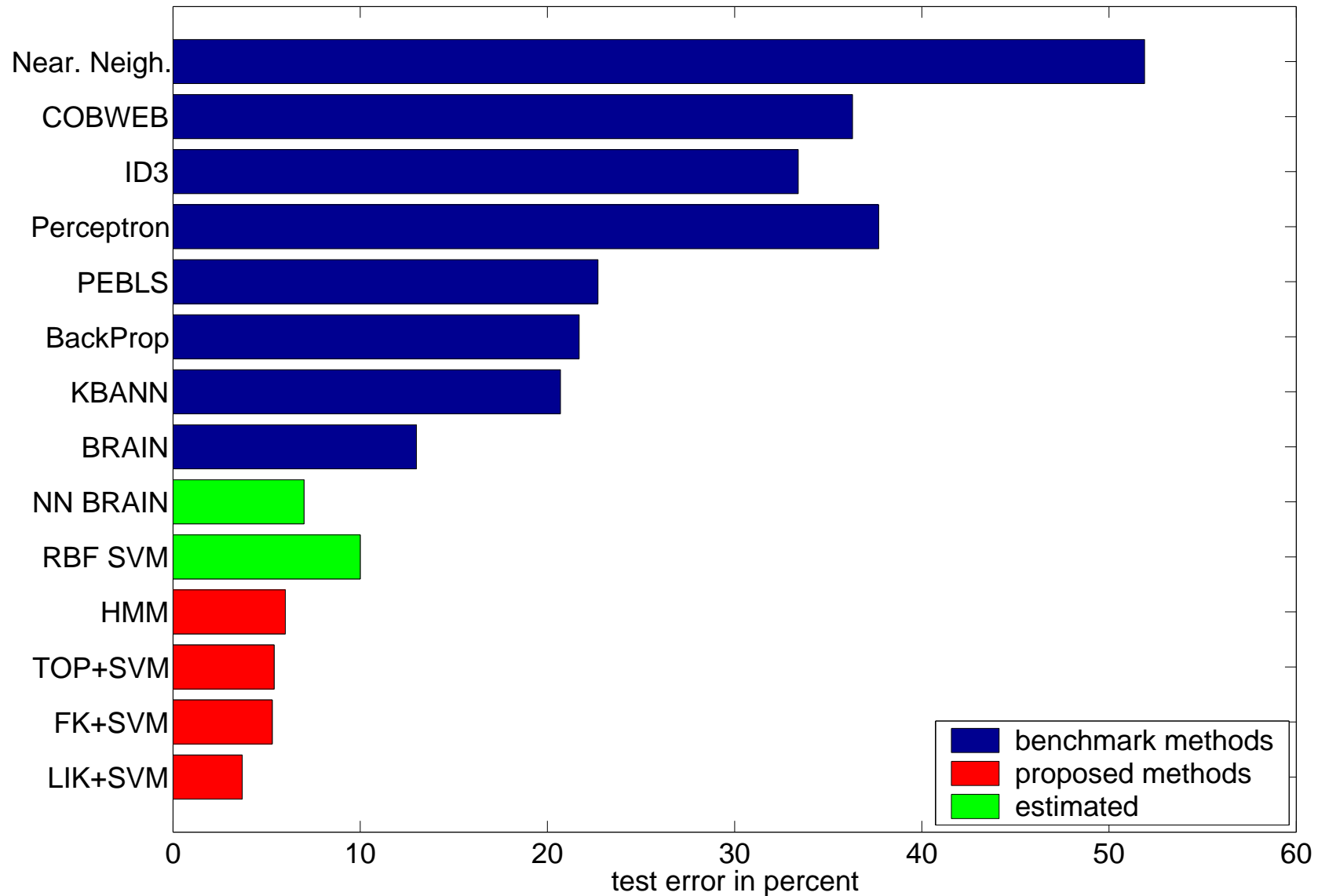
$$\mathbf{k}_{\text{TOP}}(\mathbf{x}, \mathbf{x}') = \mathbf{f}_{\hat{\boldsymbol{\theta}}}(\mathbf{x})^\top \mathbf{f}_{\hat{\boldsymbol{\theta}}}(\mathbf{x}')$$

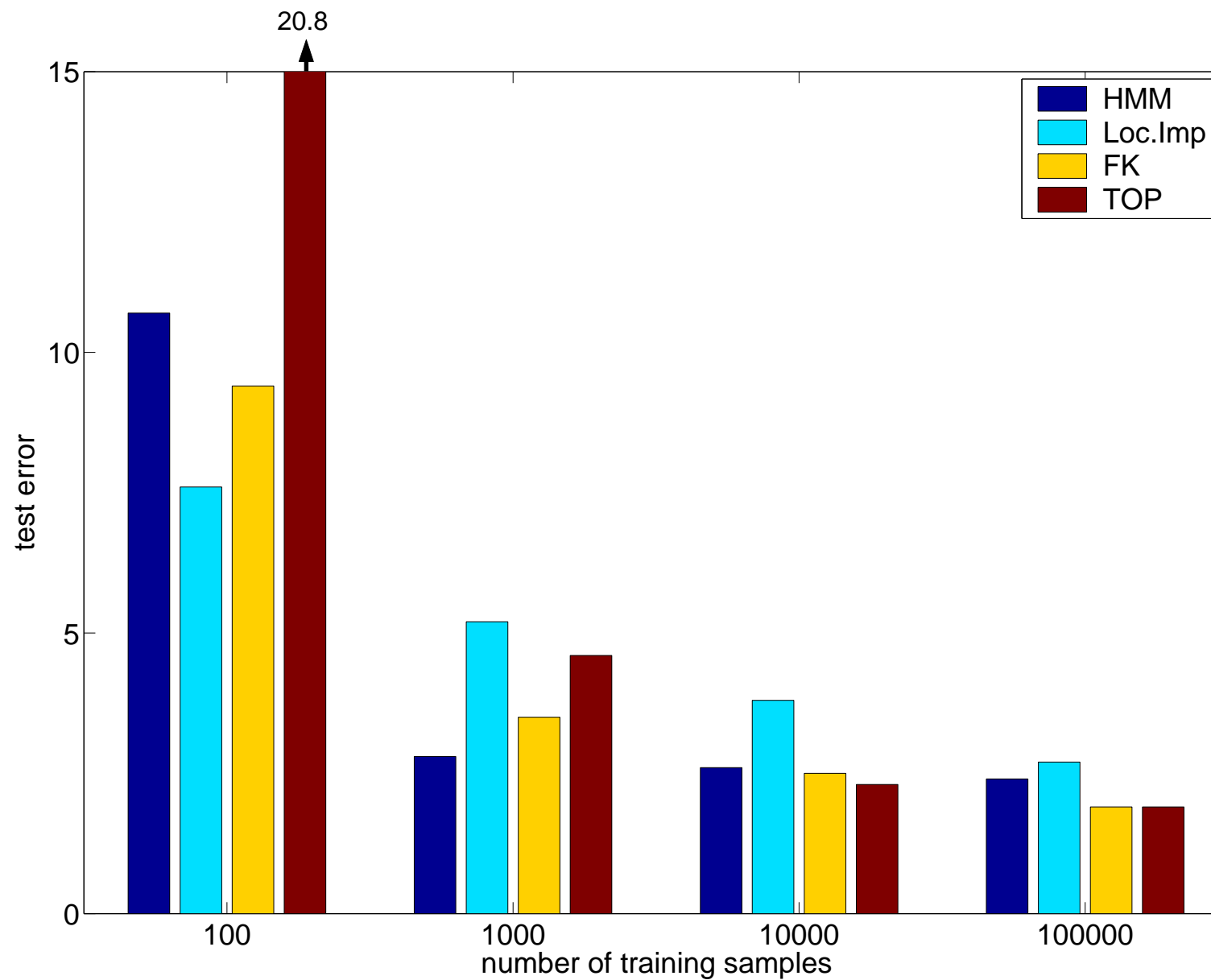
$$\mathbf{f}_{\hat{\boldsymbol{\theta}}}(\mathbf{x}) = (v(\mathbf{x}, \hat{\boldsymbol{\theta}}), \nabla_{\boldsymbol{\theta}} v(\mathbf{x}, \hat{\boldsymbol{\theta}}))^\top$$

$$v(\mathbf{x}, \hat{\boldsymbol{\theta}}) = \log(\Pr(y = +1|\mathbf{x}, \hat{\boldsymbol{\theta}})) - \log(\Pr(y = -1|\mathbf{x}, \hat{\boldsymbol{\theta}}))$$



# BENCHMARK RESULTS ON IPDATA (HUMAN GENOME)



RESULTS ON *C. elegans* ACCEPTOR SITES



## CONCLUSION

- 2 ways to engineer kernels (locality improved, from generative model)
- application to splice site recognition (**record performance**)
- benchmark results (human) and result on *C. elegans* genome
- computing time 30 CPU years (APAC Super Computer)
- Philosophical issues:
  1. explicit use of biological prior knowledge vs. use of generative model?
  2. discriminative training vs. generative models

**For more information, datasets, related papers visit:**

<http://mlg.anu.edu.au/~raetsch/splice/>