Support vector machine prediction of signal peptide cleavage site using a new class of kernels for strings

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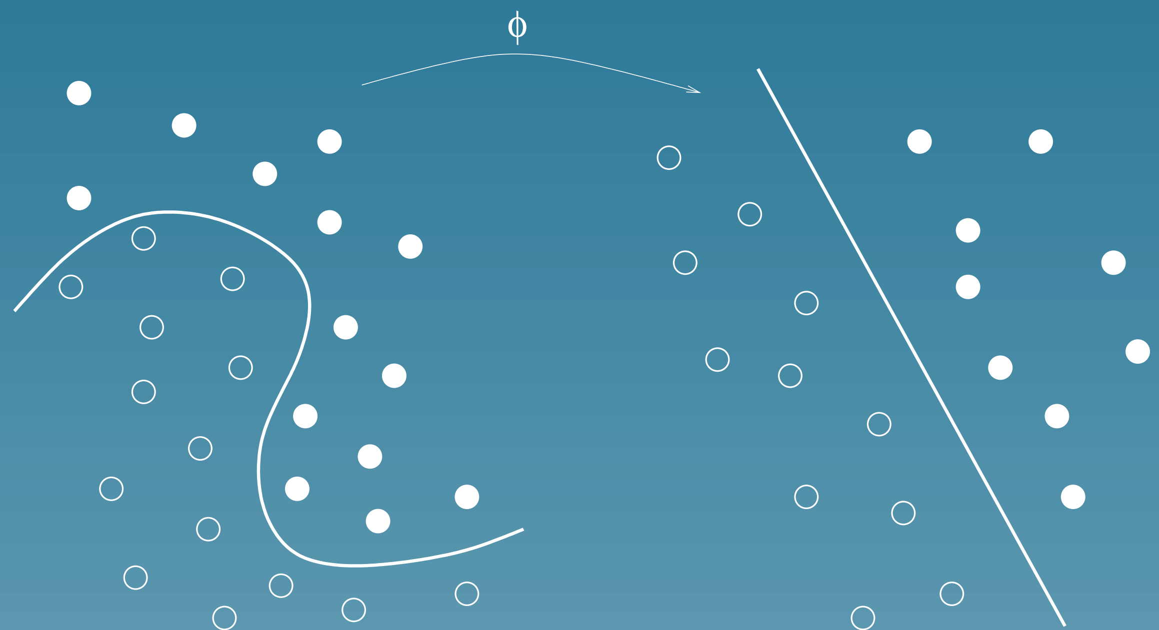
Outline

1. SVM and kernel methods
2. New kernels for bioinformatics
3. Example: signal peptide cleavage site prediction

Part 1

SVM and kernel methods

Support vector machines



- Objects to classified x mapped to a feature space
- Largest margin separating hyperplan in the feature space

The kernel trick

- Implicit definition of $x \longrightarrow \Phi(x)$ through the kernel:

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- Simple kernels can represent complex Φ
- For a given kernel, not only SVM but also clustering, PCA, ICA... possible in the feature space = kernel methods

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  - ⋆ Spectrum kernel (Leslie et al., PSB 2002)

Kernel engineering

Use prior knowledge to build the geometry of the feature space through $K(.,.)$

Part 2

New kernels for bioinfomatics

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- How to build $K(x, y)$ from $p(x)$?

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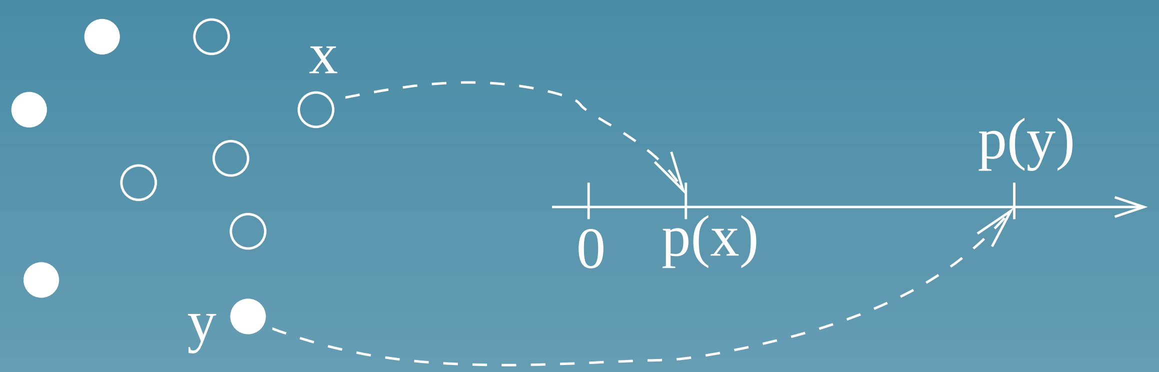

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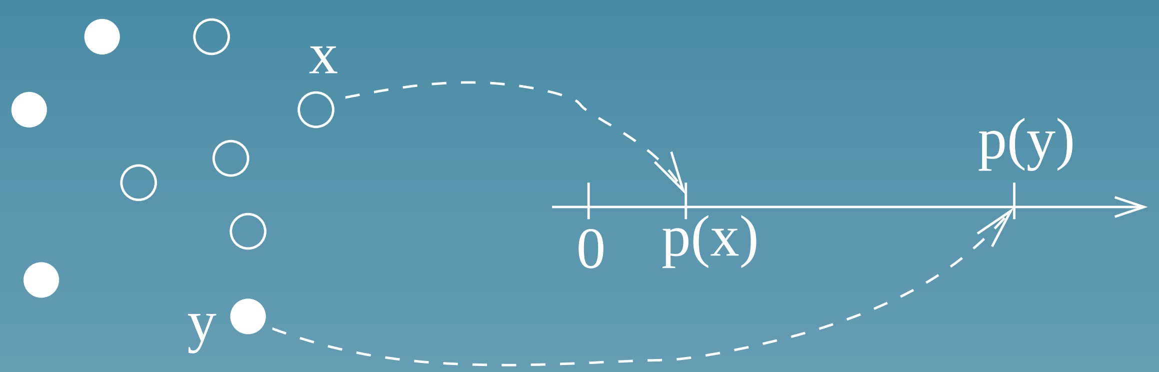

SVM = Bayesian classifier

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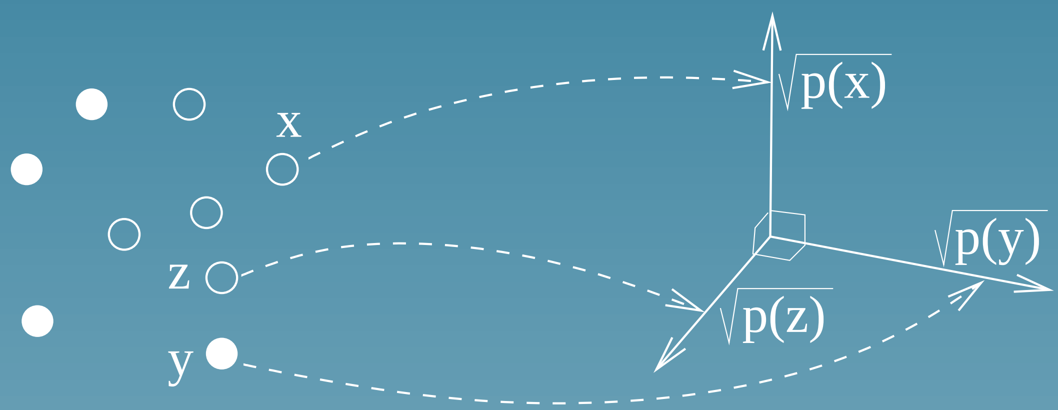

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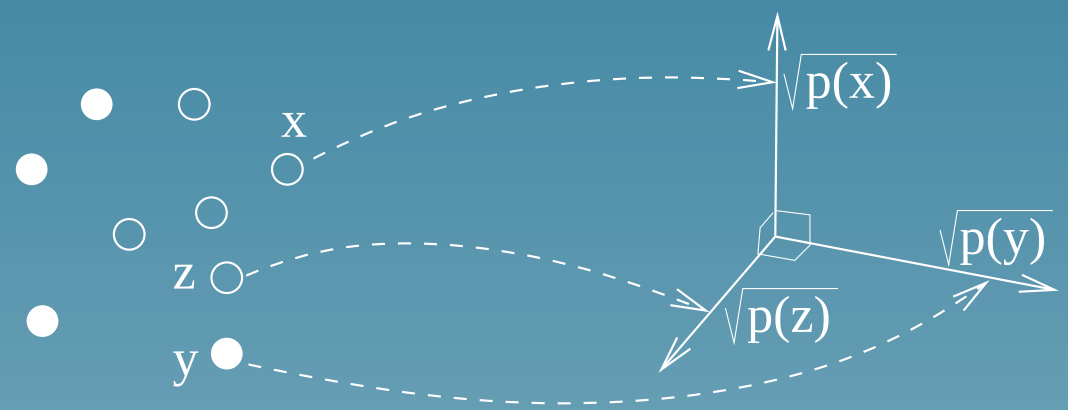

No learning

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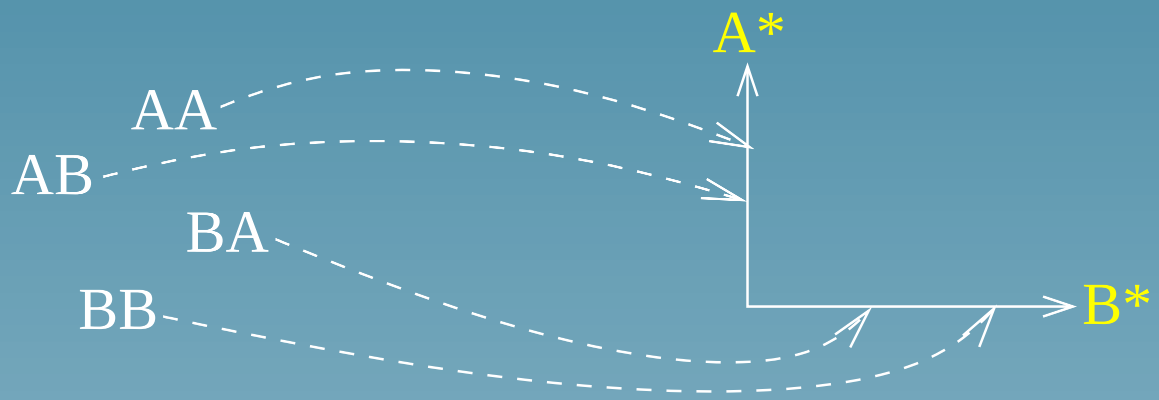

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- Interpolated kernel:

$$K_{\mathcal{V}}(x,y) = \frac{1}{|\mathcal{V}|} \sum_{I \in \mathcal{V}} K_{diag}(x_I, y_I) K_{prod}(x_{I^c}, y_{I^c})$$

Rare common subparts

For a given $p(x)$ and $p(y)$, we have:

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x and y get closer in the feature space when they share rare common subparts

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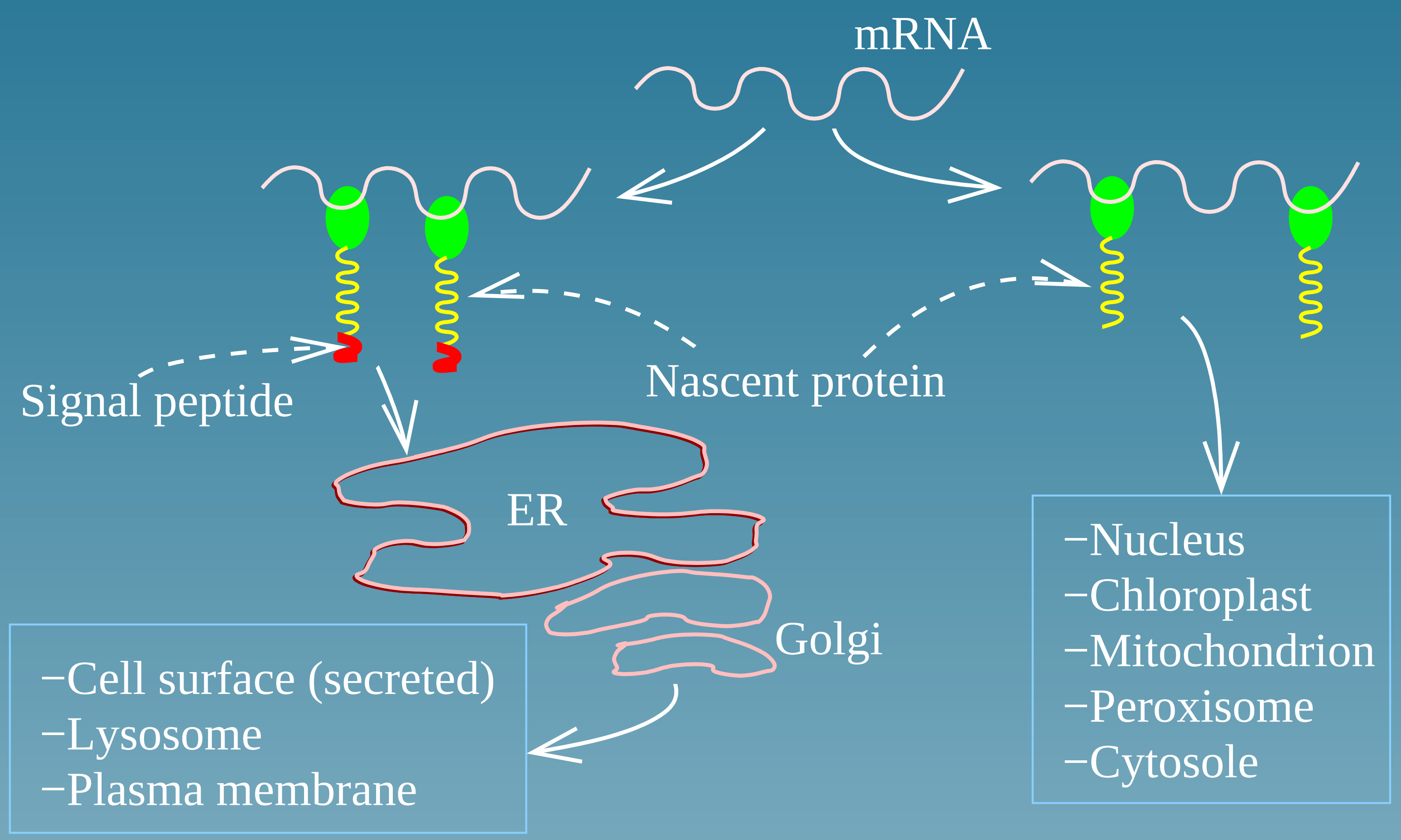
  - ⋆ product distribution $p(x) = \prod_{j=1}^{n} p_j(x_j)$.
  - ⋆ implementation in $O(n)$

Part 3

Application:
SVM prediction of signal peptide cleavage site

Secretory pathway



Signal peptides

Protein	-1 +1
(1)	MKANAKTIIAGMIALAISHTAMA EE...
(2)	MKQSTIALALLPLLFTPVTKA RT...
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- 6-12 hydrophobic residues (in yellow)
- (-3,-1) : small uncharged residues

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- Challenge : classification of aminoacids windows, positive if cleavage occurs between -1 and $+1$:

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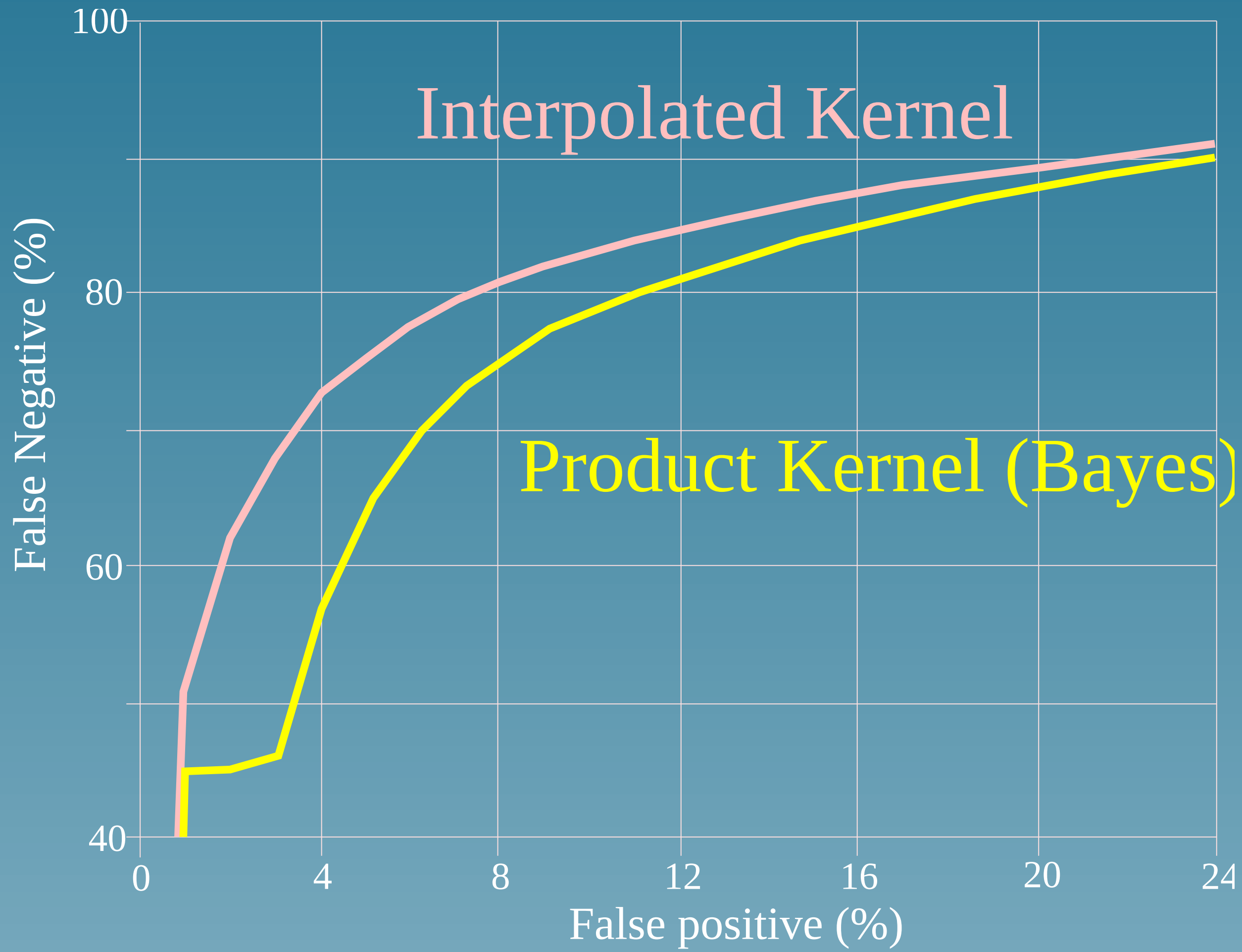
- Computation of a weight matrix:
SVM $+ K_{prod}$ (naive Bayes) vs SVM $+ K_{interpolated}$

Result: ROC curves



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- Useful when objects can be compared by comparing subparts
- Encouraging results on real-world application' "how to improve a weight matrix based classifier"
- Future work: more application-specific kernels

Acknowledgement

- Minoru Kanehisa
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