10-701 Cheat Sheet

Non-Parametric

MaxLikelihood learning window will give you delta functions, which is a kind of over fitting. Use Leave-one-out cross validation for model selection. Idea: Use some of the data to estimate density; Use other part to evaluate how well it works. Pick the parameter that works best.
$\log p(x_i|X\setminus\{x_i\}) = \log \frac{1}{n-1}\sum_{j\neq i} k(x_i,x_j)$, the sum over all points is $\frac{1}{n}\sum_{i=1}^{n}\log\left[\frac{n}{n-1}p(x_i) - \frac{1}{n-1}k(x_i,x_i)\right]$ where $p(x) = \frac{1}{n}\sum_{i=1}^{n}k(x_i,x)$.
why must we not check too many parameters? that you can overfit more; for a given dataset, a few particular parameter values might happen to do well in k-fold CV by sheer chance, where if you had a new dataset they might not do so well. Checking a reasonable number of parameter values makes you less likely to hit those "lucky" spots helps mitigate this risk.
Silverman's Rule for kernel size Use average distance from k nearest neighbors $r_i = \frac{r}{k}\sum_{x\in \mathrm{NN}(x_i,k)}\|x_i - x\|$.
Watson Nadaraya 1. estimate $p(x|y=1)$ and $p(x|y=-1)$; 2. compute by Bayes rule
$p(y|x) = \frac{p(x|y)p(y)}{p(x)} = \frac{\frac{1}{m_y}\sum_{y_i=y}k(x_i,x)\cdot\frac{m_y}{m}}{\frac{1}{m}\sum_i k(x_i,x)}$. 3. Decision boundary
$p(y=1|x) - p(y=-1|x) = \frac{\sum_j y_j k(x_j,x)}{\sum_i k(x_i,x)} = \sum_j y_j \frac{k(x_j,x)}{\sum_i k(x_i,x)}$
Actually, we assume that p(x—y) is equal to $1/m_y * \sum_y k(x_i,x)$. Using this definition, we can see $p(x,-1)+p(x,1) = p(x|-1)p(-1)+p(x|1)p(1) = p(x)$. This can be incorporated into the regression framework in chap 6 of PRML. Where we define $f(x-x_n, t\neq t_n) = 0$, and $f(x-x_n, t=t_n) = f(x-x_n)$. Using this definition, we can derive all the probabilities on this slide. (see my handwritten notes on chap 6 of PRML).
Regression case is the same equation.
kNN Let optimal error rate be p. Given unlimited **iid** data, 1NN's error rate is $\leq 2p(1-p)$.

Matrix Cookbook

$\frac{\partial \boldsymbol{x}^T\boldsymbol{a}}{\partial \boldsymbol{x}} = \frac{\partial \boldsymbol{a}^T\boldsymbol{x}}{\partial \boldsymbol{x}} = \boldsymbol{a}$
$\frac{\partial \boldsymbol{a}^T\boldsymbol{X}\boldsymbol{b}}{\partial \boldsymbol{X}} = \boldsymbol{a}\boldsymbol{b}^T$, $\frac{\partial \boldsymbol{a}^T\boldsymbol{X}^T\boldsymbol{b}}{\partial \boldsymbol{X}} = \boldsymbol{b}\boldsymbol{a}^T$, $\frac{\partial \boldsymbol{a}^T(\boldsymbol{X}^T|\boldsymbol{X})\boldsymbol{a}}{\partial \boldsymbol{X}} = \boldsymbol{a}\boldsymbol{a}^T$
$W\in \boldsymbol{S}$, $\frac{\partial}{\partial \boldsymbol{s}}(\boldsymbol{x}-\boldsymbol{A}\boldsymbol{s})^T\boldsymbol{W}(\boldsymbol{x}-\boldsymbol{A}\boldsymbol{s}) = -2\boldsymbol{A}^T\boldsymbol{W}(\boldsymbol{x}-\boldsymbol{A}\boldsymbol{s})$,
$\frac{\partial}{\partial \boldsymbol{x}}(\boldsymbol{x}-\boldsymbol{s})^T\boldsymbol{W}(\boldsymbol{x}-\boldsymbol{s}) = 2\boldsymbol{W}(\boldsymbol{x}-\boldsymbol{s})$,
$\frac{\partial}{\partial \boldsymbol{s}}(\boldsymbol{x}-\boldsymbol{s})^T\boldsymbol{W}(\boldsymbol{x}-\boldsymbol{s}) = -2\boldsymbol{W}(\boldsymbol{x}-\boldsymbol{s})$,
$\frac{\partial}{\partial \boldsymbol{x}}(\boldsymbol{x}-\boldsymbol{A}\boldsymbol{s})^T\boldsymbol{W}(\boldsymbol{x}-\boldsymbol{A}\boldsymbol{s}) = 2\boldsymbol{W}(\boldsymbol{x}-\boldsymbol{A}\boldsymbol{s})$,
$\frac{\partial}{\partial \boldsymbol{A}}(\boldsymbol{x}-\boldsymbol{A}\boldsymbol{s})^T\boldsymbol{W}(\boldsymbol{x}-\boldsymbol{A}\boldsymbol{s}) = -2\boldsymbol{W}(\boldsymbol{x}-\boldsymbol{A}\boldsymbol{s})\boldsymbol{s}^T$,

Classifers and Regressors

Naive Bayes Conditionally independent:
$P(x_1,x_2,\ldots|C) = \prod_i P(x_i|C)$. One way to avoid divide by zero: add $(1,1,\ldots,1)$ and $(0,0,\ldots,0)$ to both classes.
Learns $P(x_i|y)$ for *Discrete* x_i – $P(x_i|y) = \frac{\#D(X_i=x_i,Y=y)}{\#D(Y=y)}$
For smoothing, use $P(x_i|y) = \frac{\#D(X_i=x_i,Y=y)+k}{\#D(Y=y)+n_i k}$, where n_i is the number of different possible values for X_i (In practice problem set, Jing Xiang used $k=1$?) *Continuous* x_i – Can use any PDF, but usually use Gaussian $P(x_i|y) = \mathcal{N}(\mu_{X_i|y}, \sigma^2_{X_i|y})$, where $\mu_{X_i|y}$ and $\sigma_{X_i|y}$ are, respectively, the average and variance of X_i for all data points where $Y=y$. The Gaussian distribution already provides smoothing.

Perceptron Produces linear decision boundaries. *Classifies* using $\hat{y} = X_{test}\,w + b$ *Learns* w and b by updating w whenever $y_i(w^Tx_i+b)\leq 0$ (i.e. incorrectly classified). Updates as $w \leftarrow w + x_iy_i, b\leftarrow b+y_i$ Repeat until all examples are correctly classified. w is some linear combination $\sum_i \alpha_i x_i(y_i * x_i)$ of data points, and decision boundary is the linear hyperplane $f(x) = w^Tx+b$. **Note** that the perceptron is the same as stochastic gradient descent with a hinge loss function of $max(0, 1-y_i[<w,x_i>+b])$ (**is this loss function right**).

Convergence of perceptron proof 1 by holy shit smola
Convergence of perceptron proof 2 by gordon
