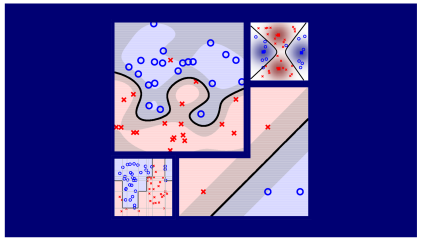
Machine Learning Techniques
(機器學習技法)



Lecture 6: Support Vector Regression

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Roadmap

1. Embedding Numerous Features: Kernel Models

Lecture 5: Kernel Logistic Regression

two-level learning for **SVM-like sparse model** for soft classification, or using **representer theorem** with **regularized logistic error** for dense model

Lecture 6: Support Vector Regression

- Kernel Ridge Regression
- Support Vector Regression Primal
- Support Vector Regression Dual
- Summary of Kernel Models

2. Combining Predictive Features: Aggregation Models
3. Distilling Implicit Features: Extraction Models

Recall: Representer Theorem

for any L2-regularized linear model

$$\min_{\mathbf{w}} \quad \frac{\lambda}{N}\mathbf{w}^T\mathbf{w} + \frac{1}{N}\sum_{n=1}^{N} \text{err}(y_n, \mathbf{w}^T\mathbf{z}_n)$$

optimal $\mathbf{w}_* = \sum_{n=1}^{N} \beta_n \mathbf{z}_n$.
—any L2-regularized linear model can be **kernelized**!

regression with squared error

$$\text{err}(y, \mathbf{w}^T\mathbf{z}) = (y - \mathbf{w}^T\mathbf{z})^2$$

—analytic solution for linear/ridge regression

analytic solution for **kernel** ridge regression?

Kernel Ridge Regression Problem

solving ridge regression $\min_{\mathbf{w}} \frac{\lambda}{N}\mathbf{w}^T\mathbf{w} + \frac{1}{N}\sum_{n=1}^{N}(y_n - \mathbf{w}^T\mathbf{z}_n)^2$

yields optimal solution $\mathbf{w}_* = \sum_{n=1}^{N}\beta_n\mathbf{z}_n$

with out loss of generality, can solve for optimal β instead of $\mathbf{w}$

$$\min_{\beta} \quad \frac{\lambda}{N}\underbrace{\sum_{n=1}^{N}\sum_{m=1}^{N}\beta_n\beta_m K(\mathbf{x}_n,\mathbf{x}_m)}_{\text{regularization of } \beta \text{ on } K\text{-based regularizer}} + \frac{1}{N}\underbrace{\sum_{n=1}^{N}\left(y_n - \sum_{m=1}^{N}\beta_m K(\mathbf{x}_n,\mathbf{x}_m)\right)^2}_{\text{linear regression of } \beta \text{ on } K\text{-based features}}$$

$$= \frac{\lambda}{N}\beta^T\mathrm{K}\beta + \frac{1}{N}\left(\beta^T\mathrm{K}^T\mathrm{K}\beta - 2\beta^T\mathrm{K}^T\mathbf{y} + \mathbf{y}^T\mathbf{y}\right)$$

kernel ridge regression:
use **representer theorem** for kernel trick on **ridge regression**

Solving Kernel Ridge Regression

$$E_{\text{aug}}(\boldsymbol{\beta}) = \frac{\lambda}{N}\boldsymbol{\beta}^T\mathrm{K}\boldsymbol{\beta} + \frac{1}{N}\left(\boldsymbol{\beta}^T\mathrm{K}^T\mathrm{K}\boldsymbol{\beta} - 2\boldsymbol{\beta}^T\mathrm{K}^T\mathbf{y} + \mathbf{y}^T\mathbf{y}\right)$$

$$\nabla E_{\text{aug}}(\boldsymbol{\beta}) = \frac{2}{N}\left(\lambda\mathrm{K}^T\mathrm{I}\boldsymbol{\beta} + \mathrm{K}^T\mathrm{K}\boldsymbol{\beta} - \mathrm{K}^T\mathbf{y}\right) = \frac{2}{N}\mathrm{K}^T\left((\lambda\mathrm{I} + \mathrm{K})\boldsymbol{\beta} - \mathbf{y}\right)$$

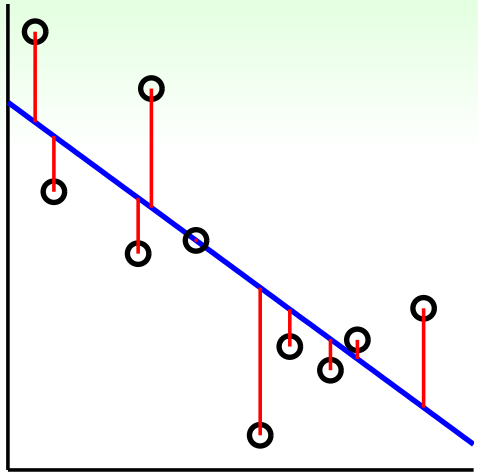
want $\nabla E_{\text{aug}}(\boldsymbol{\beta}) = \mathbf{0}$: one analytic solution

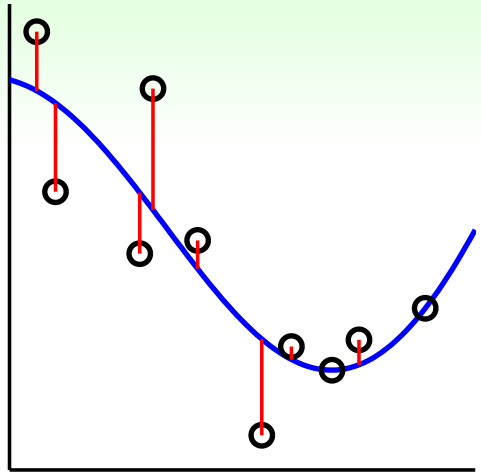
$$\boldsymbol{\beta} = (\lambda\mathrm{I} + \mathrm{K})^{-1}\mathbf{y}$$

- $(\cdot)^{-1}$ always exists for $\lambda > 0$, because K positive semi-definite (**Mercer's condition, remember? :-)**)
- time complexity: $O(N^3)$ with simple **dense** matrix inversion

can now do **non-linear regression** 'easily'

Linear versus Kernel Ridge Regression





linear ridge regression

$$\mathbf{w} = (\lambda \mathrm{I} + \mathrm{X}^T\mathrm{X})^{-1}\mathrm{X}^T\mathbf{y}$$

- more restricted
- $O(d^3 + d^2N)$ training;
  $O(d)$ prediction
  —**efficient when** $N \gg d$

kernel ridge regression

$$\beta = (\lambda \mathrm{I} + \mathrm{K})^{-1}\mathbf{y}$$

- **more flexible** with K
- $O(N^3)$ training;
  $O(N)$ prediction
  —hard for big data

linear versus **kernel**:
trade-off between **efficiency** and **flexibility**

Fun Time

After getting the optimal β from kernel ridge regression based on some kernel function K, what is the resulting $g(\mathbf{x})$?

1. $\sum_{n=1}^{N} \beta_n K(\mathbf{x}_n, \mathbf{x})$
2. $\sum_{n=1}^{N} y_n \beta_n K(\mathbf{x}_n, \mathbf{x})$
3. $\sum_{n=1}^{N} \beta_n K(\mathbf{x}_n, \mathbf{x}) + \lambda$
4. $\sum_{n=1}^{N} y_n \beta_n K(\mathbf{x}_n, \mathbf{x}) + \lambda$

Fun Time

After getting the optimal β from kernel ridge regression based on some kernel function K, what is the resulting $g(\mathbf{x})$?

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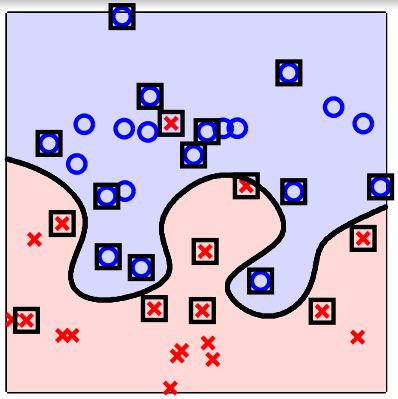
3. $\sum_{n=1}^{N} \beta_n K(\mathbf{x}_n, \mathbf{x}) + \lambda$
4. $\sum_{n=1}^{N} y_n \beta_n K(\mathbf{x}_n, \mathbf{x}) + \lambda$

Reference Answer: 1

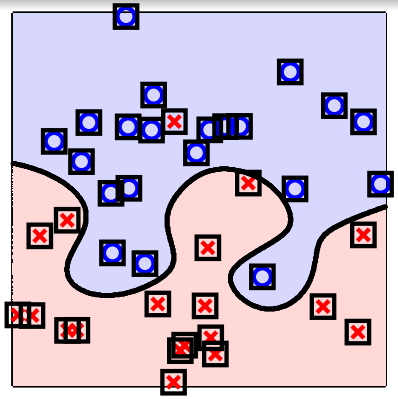
Recall that the optimal $\mathbf{w} = \sum_{n=1}^{N} \beta_n \mathbf{z}_n$ by representer theorem and $g(\mathbf{x}) = \mathbf{w}^T \mathbf{z}$. The answer comes from combining the two equations with the kernel trick.

Soft-Margin SVM versus Least-Squares SVM

least-squares SVM (LSSVM)
= **kernel ridge regression** for classification



soft-margin Gaussian SVM



Gaussian LSSVM

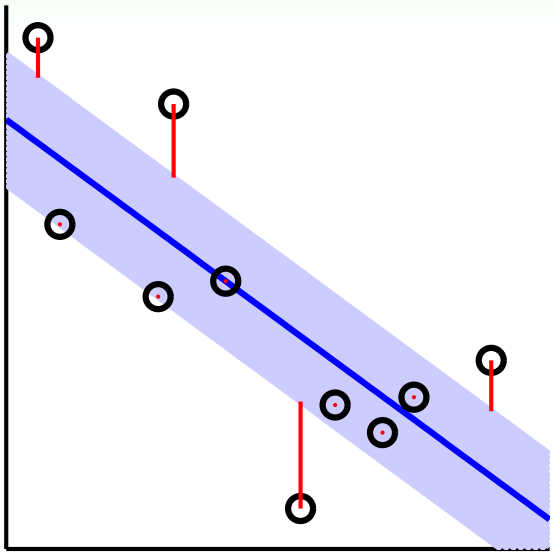
- LSSVM: similar boundary, **many more SVs**
  $\Longrightarrow$ slower prediction, **dense β (BIG g)**
- dense β: LSSVM, kernel LogReg;
  sparse α: standard SVM

want: **sparse** β like standard SVM

Tube Regression

will consider **tube regression**

- within a tube: **no error**
- outside a tube: **error** by distance to tube



error measure:

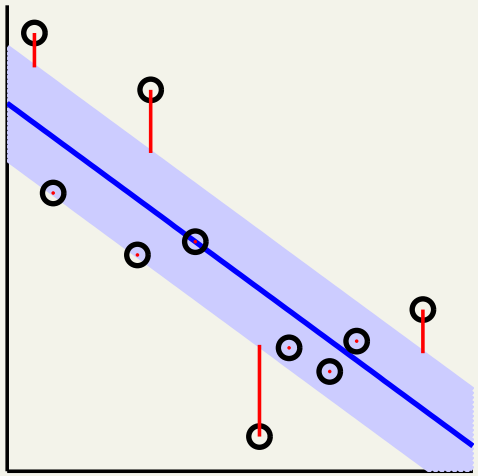
$$\text{err}(y, s) \quad = \quad \max(0, |s - y| - \epsilon)$$

- $|s - y| \leq \epsilon$: 0
- $|s - y| > \epsilon$: $|s - y| - \epsilon$

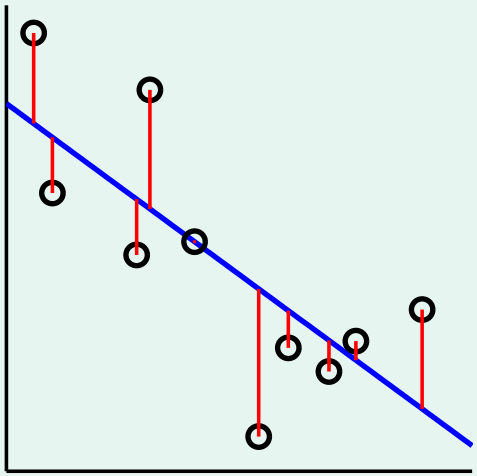
—usually called **ϵ-insensitive error** with $\epsilon > 0$

todo: L2-regularized **tube regression**
to get **sparse β**

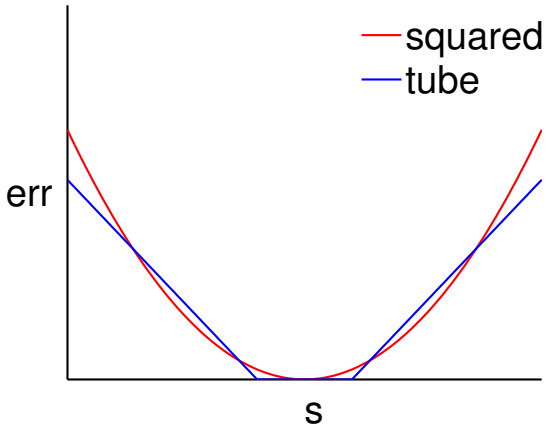
Tube versus Squared Regression



tube: $\text{err}(y, s) = \max(0, |s - y| - \epsilon)$



squared: $\text{err}(y, s) = (s - y)^2$



tube $\approx$ squared when $|s - y|$ small
& **less affected by outliers**

L2-Regularized Tube Regression

$$\min_{\mathbf{w}} \quad \frac{\lambda}{N}\mathbf{w}^T\mathbf{w} + \frac{1}{N}\sum_{n=1}^{N} \max\left(0, |\mathbf{w}^T\mathbf{z}_n - y_n| - \epsilon\right)$$

Regularized Tube Regr.

$\min \frac{\lambda}{N}\mathbf{w}^T\mathbf{w} + \frac{1}{N}\sum$ tube violation

- unconstrained,
  but max **not differentiable**
- 'representer' to kernelize,
  but **no obvious sparsity**

standard SVM

$\min \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum$ margin vio.

- not differentiable,
  but **QP**
- dual to kernelize,
  KKT conditions $\Rightarrow$ **sparsity**

will mimic standard SVM derivation:

$$\min_{b,\mathbf{w}} \quad \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{n=1}^{N} \max\left(0, |\mathbf{w}^T\mathbf{z}_n + b - y_n| - \epsilon\right)$$

Standard Support Vector Regression Primal

$$\min_{b,\mathbf{w}} \quad \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{n=1}^{N} \max\left(0, |\mathbf{w}^T\mathbf{z}_n + b - y_n| - \epsilon\right)$$

mimicking standard SVM

$$\min_{b,\mathbf{w},\boldsymbol{\xi}} \quad \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{n=1}^{N} \xi_n$$

$$s.t. \quad |\mathbf{w}^T\mathbf{z}_n + b - y_n| \le \epsilon + \xi_n$$

$$\xi_n \ge 0$$

making constraints linear

$$\frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{n=1}^{N} \left(\xi_n^\vee + \xi_n^\wedge\right)$$

$$-\epsilon - \xi_n^\vee \le y_n - \mathbf{w}^T\mathbf{z}_n - b \le \epsilon + \xi_n^\wedge$$

$$\xi_n^\vee \ge 0, \xi_n^\wedge \ge 0$$

Support Vector Regression (SVR) primal:
minimize regularizer + (upper tube violations $\xi_n^\wedge$ & lower violations $\xi_n^\vee$)

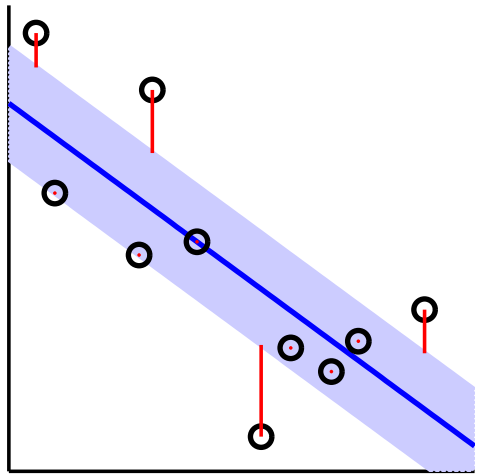
Quadratic Programming for SVR

$$\min_{b,\mathbf{w},\boldsymbol{\xi}^\vee,\boldsymbol{\xi}^\wedge} \quad \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{n=1}^{N}\left(\xi_n^\vee + \xi_n^\wedge\right)$$

$$s.t. \quad -\epsilon - \xi_n^\vee \le y_n - \mathbf{w}^T\mathbf{z}_n - b \le \epsilon + \xi_n^\wedge$$

$$\xi_n^\vee \ge 0, \xi_n^\wedge \ge 0$$

- parameter C: trade-off of regularization & tube violation
- parameter ϵ: vertical tube width —one more parameter to choose!
- QP of $\tilde{d} + 1 + 2N$ variables, $2N + 2N$ constraints



next: remove dependence on $\tilde{d}$ by SVR primal $\Rightarrow$ **dual**?

Fun Time

Consider solving support vector regression with $\epsilon = 0.05$. At the optimal solution, assume that $\mathbf{w}^T\mathbf{z}_1 + b = 1.234$ and $y_1 = 1.126$. What is $\xi_1^\vee$ and $\xi_1^\wedge$?

1. $\xi_1^\vee = 0.108, \xi_1^\wedge = 0.000$
2. $\xi_1^\vee = 0.000, \xi_1^\wedge = 0.108$
3. $\xi_1^\vee = 0.058, \xi_1^\wedge = 0.000$
4. $\xi_1^\vee = 0.000, \xi_1^\wedge = 0.058$

Fun Time

Consider solving support vector regression with $\epsilon = 0.05$. At the optimal solution, assume that $\mathbf{w}^T\mathbf{z}_1 + b = 1.234$ and $y_1 = 1.126$. What is $\xi_1^\vee$ and $\xi_1^\wedge$?

1. $\xi_1^\vee = 0.108, \xi_1^\wedge = 0.000$
2. $\xi_1^\vee = 0.000, \xi_1^\wedge = 0.108$
3. $\xi_1^\vee = 0.058, \xi_1^\wedge = 0.000$
4. $\xi_1^\vee = 0.000, \xi_1^\wedge = 0.058$

Reference Answer: 3

$y_1 - \mathbf{w}^T\mathbf{z}_1 - b = -0.108 < -0.05$, which means that there is a lower tube violation of amount 0.058. When there is a lower tube violation on some example, trivially there is no upper tube violation.

Lagrange Multipliers $\alpha^{\wedge}$ & $\alpha^{\vee}$

objective function $\frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{n=1}^{N}\left(\xi_n^{\vee} + \xi_n^{\wedge}\right)$

Lagrange multiplier $\alpha_n^{\wedge}$ for $y_n - \mathbf{w}^T\mathbf{z}_n - b \le \epsilon + \xi_n^{\wedge}$

Lagrange multiplier $\alpha_n^{\vee}$ for $-\epsilon - \xi_n^{\vee} \le y_n - \mathbf{w}^T\mathbf{z}_n - b$

Some of the KKT Conditions

- $\frac{\partial \mathcal{L}}{\partial w_i} = 0$: $\mathbf{w} = \sum_{n=1}^{N} \underbrace{(\alpha_n^{\wedge} - \alpha_n^{\vee})}_{\beta_n}\mathbf{z}_n$; $\frac{\partial \mathcal{L}}{\partial b} = 0$: $\sum_{n=1}^{N}(\alpha_n^{\wedge} - \alpha_n^{\vee}) = 0$
- complementary slackness:

$$\alpha_n^{\wedge}(\epsilon + \xi_n^{\wedge} - y_n + \mathbf{w}^T\mathbf{z}_n + b) = 0$$
$$\alpha_n^{\vee}(\epsilon + \xi_n^{\vee} + y_n - \mathbf{w}^T\mathbf{z}_n - b) = 0$$

standard dual can be derived
using the same steps as Lecture 4

SVM Dual and SVR Dual

$$\begin{aligned}\min \quad & \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{n=1}^{N}\xi_n \\ \text{s.t.} \quad & y_n(\mathbf{w}^T\mathbf{z}_n + b) \geq 1 - \xi_n \\ & \xi_n \geq 0\end{aligned}$$

$$\begin{aligned}\min \quad & \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{n=1}^{N}(\xi_n^\wedge + \xi_n^\vee) \\ \text{s.t.} \quad & 1(y_n - \mathbf{w}^T\mathbf{z}_n - b) \leq \epsilon + \xi_n^\wedge \\ & 1(\mathbf{w}^T\mathbf{z}_n + b - y_n) \leq \epsilon + \xi_n^\vee \\ & \xi_n^\wedge \geq 0, \xi_n^\vee \geq 0\end{aligned}$$

$$\begin{aligned}\min \quad & \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N}\alpha_n\alpha_m y_n y_m K(\mathbf{x}_n, \mathbf{x}_m) \\ & -\sum_{n=1}^{N} 1 \cdot \alpha_n \\ \text{s.t.} \quad & \sum_{n=1}^{N} y_n\alpha_n = 0 \\ & 0 \leq \alpha_n \leq C\end{aligned}$$

$$\begin{aligned}\min \quad & \frac{1}{2}\sum_{n=1}^{N}\sum_{m=1}^{N}(\alpha_n^\wedge - \alpha_n^\vee)(\alpha_m^\wedge - \alpha_m^\vee)k_{n,m} \\ & +\sum_{n=1}^{N}\left((\epsilon - y_n)\cdot\alpha_n^\wedge + (\epsilon + y_n)\cdot\alpha_n^\vee\right) \\ \text{s.t.} \quad & \sum_{n=1}^{N} 1\cdot(\alpha_n^\wedge - \alpha_n^\vee) = 0 \\ & 0 \leq \alpha_n^\wedge \leq C, 0 \leq \alpha_n^\vee \leq C\end{aligned}$$

similar QP, **solvable by similar solver**

Sparsity of SVR Solution

- $\mathbf{w} = \sum_{n=1}^{N} \underbrace{(\alpha_n^\wedge - \alpha_n^\vee)}_{\beta_n} \mathbf{z}_n$
- complementary slackness:

$$\begin{aligned} \alpha_n^\wedge(\epsilon + \xi_n^\wedge - y_n + \mathbf{w}^T\mathbf{z}_n + b) &= 0 \\ \alpha_n^\vee(\epsilon + \xi_n^\vee + y_n - \mathbf{w}^T\mathbf{z}_n - b) &= 0 \end{aligned}$$

- strictly within tube $|\mathbf{w}^T\mathbf{z}_n + b - y_n| < \epsilon$
  $\implies \xi_n^\wedge = 0$ and $\xi_n^\vee = 0$
  $\implies (\epsilon + \xi_n^\wedge - y_n + \mathbf{w}^T\mathbf{z}_n + b) \neq 0$ and $(\epsilon + \xi_n^\vee + y_n - \mathbf{w}^T\mathbf{z}_n - b) \neq 0$
  $\implies \alpha_n^\wedge = 0$ and $\alpha_n^\vee = 0$
  $\implies \beta_n = 0$
- SVs ($\beta_n \neq 0$): **on or outside tube**

SVR: allows **sparse β**

Fun Time

What is the number of variables within the QP problem of SVR dual?

1. $\tilde{d} + 1$
2. $\tilde{d} + 1 + 2N$
3. N
4. $2N$

Fun Time

What is the number of variables within the QP problem of SVR dual?

1. $\tilde{d} + 1$
2. $\tilde{d} + 1 + 2N$
3. N
4. $2N$

Reference Answer: 4

There are N variables within $\boldsymbol{\alpha}^{\vee}$, and another N in $\boldsymbol{\alpha}^{\wedge}$.

Map of Linear Models

PLA/pocket

minimize $\text{err}_{0/1}$ specially

linear SVR

minimize regularized err_{TUBE} by QP

linear soft-margin SVM

minimize regularized $\widehat{\text{err}}_{\text{SVM}}$ by QP

linear ridge regression

minimize regularized err_{SQR} analytically

regularized logistic regression

minimize regularized err_{CE} by GD/SGD

second row: popular in **LIBLINEAR**

Map of Linear/Kernel Models

PLA/pocket	linear SVR	
linear soft-margin SVM	linear ridge regression	regularized logistic regression
	kernel ridge regression	kernel logistic regression
	kernelized linear ridge regression	kernelized regularized logistic regression
SVM	SVR	probabilistic SVM
minimize SVM dual by QP	minimize SVR dual by QP	run SVM-transformed logistic regression

fourth row: popular in **LIBSVM**

Map of Linear/Kernel Models

PLA/pocket	linear SVR	
linear soft-margin SVM	linear ridge regression	regularized logistic regression
	kernel ridge regression	kernel logistic regression
SVM	SVR	probabilistic SVM

first row: less used due to **worse performance**
third row: less used due to **dense β**

Kernel Models

possible kernels:

polynomial, Gaussian, . . ., your design (with Mercer's condition),

coupled with

	kernel ridge regression	kernel logistic regression
SVM	SVR	probabilistic SVM

powerful extension of linear models
—*with great power comes great responsibility*
in **Spiderman, remember? :-)**

Fun Time

Which of the following model is less used in practice?

1. pocket
2. ridge regression
3. (linear or kernel) soft-margin SVM
4. regularized logistic regression

Fun Time

Which of the following model is less used in practice?

1. pocket
2. ridge regression
3. (linear or kernel) soft-margin SVM
4. regularized logistic regression

Reference Answer: 1

The pocket algorithm generally does not perform better than linear soft-margin SVM, and hence is less used in practice.

Summary

1. Embedding Numerous Features: Kernel Models

Lecture 6: Support Vector Regression

- Kernel Ridge Regression
  representer theorem on ridge regression
- Support Vector Regression Primal
  minimize regularized tube errors
- Support Vector Regression Dual
  a QP similar to SVM dual
- Summary of Kernel Models
  with great power comes great responsibility

2. Combining Predictive Features: Aggregation Models
   - **next: making cocktail from learning models**
3. Distilling Implicit Features: Extraction Models