

Regularization & Sparsity

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IN4320 MACHINE LEARNING



Outline

- Data & generalization →
 - Empirical risk →
 - Regression →
 - Stability →
 - Regularization →
 - Sparsity →
 - Time for more Qs?

- Q : indicates a Q you should be able to answer...



The Setting

- Say we have N feature vectors x_i and corresponding outputs or targets y_i
- Say we want to estimate a functional relationship $f(x; w) \approx y$, with parameters w , to predict correct outputs to new and unseen feature vectors
- Q : how could we do this?



Empirical Risk

- All we have is N observations, so we could try and find a w that at least works well on these
- "Working well" is expressed in terms of loss ℓ
- Total loss on all points is the empirical risk

$$\sum_{i=1}^N \ell(f(x_i; w), y_i)$$



Minimizing Empirical Risk

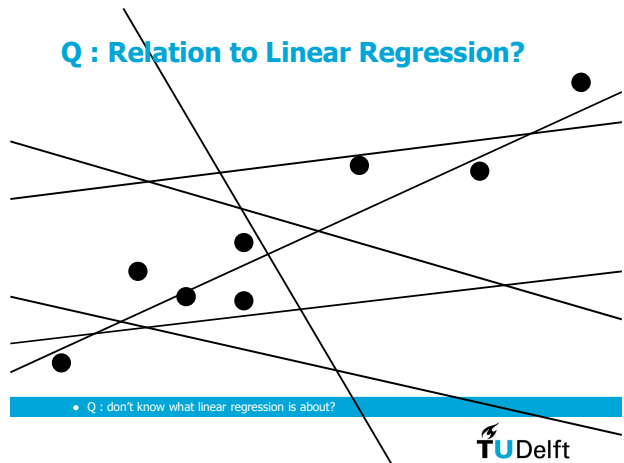
- One often considers the solution with the minimal empirical risk

$$\operatorname{argmin}_w \sum_{i=1}^N \ell(f(x_i; w), y_i)$$

- Q : approaches you know that fit formulation?



Q : Relation to Linear Regression?



- Q : don't know what linear regression is about?



Linear Least Squares Regression

- Standard regression solves

$$\min_w \sum_{i=1}^N (f(x_i, w) - y_i)^2$$

- Where f is linear in x : $f(x; w) = w^T x$



Linear Least Squares Regression

- Solution

$$w = (XX^T)^{-1}XY^T$$

X matrix with all x_i in columns; Y output row

- In case of too few observations, we need pseudo-inverse : $w = (XX^T)^+XY^T$
- Understand how to come to these solutions!!!



Many Dimensions / Few Observations

- What happens with relatively few observations in relatively high dimensions?
- E.g. assume average x_i is 0 and consider $w = (XX^T)^{-1}XY^T = (\frac{1}{N}XX^T)^{-1}(\frac{1}{N}XY^T)$
 - Q : eigenvalues of the covariance matrix?
 - Q : effect of this on the vector XY^T ?
 - Do experiments if you do not see or believe...



Many Dimensions / Few Observations

- Solution $w = (XX^T)^{-1}XY^T$ is unstable and can be all over the place
- Generalization to unseen data can, and will often, be very bad
- Q : how to stabilize the solution? Any ideas?



Stabilization, One Way to Perform

- Idea : keep eigenvalues away from 0
- Add identity to XX^T : $w = (XX^T + \lambda I)^{-1}XY^T$
- Q : why consider the identity?



Stabilization as Regularization

- Idea : keep eigenvalues away from 0
- Add identity to XX^T : $w = (XX^T + \lambda I)^{-1}XY^T$
- This choice of w is, in fact, the solution of

$$\min_w \sum_{i=1}^N (f(x_i, w) - y_i)^2 + \lambda \|w\|^2$$



An Equivalent View

- Instead of solving

$$\min_w \sum_{i=1}^N (f(x_i, w) - y_i)^2 + \lambda \|w\|^2$$

one can also solve

$$\begin{aligned} \min_w \sum_{i=1}^N (f(x_i, w) - y_i)^2 \\ \text{s. t. } \|w\|^2 \leq \tau \end{aligned}$$



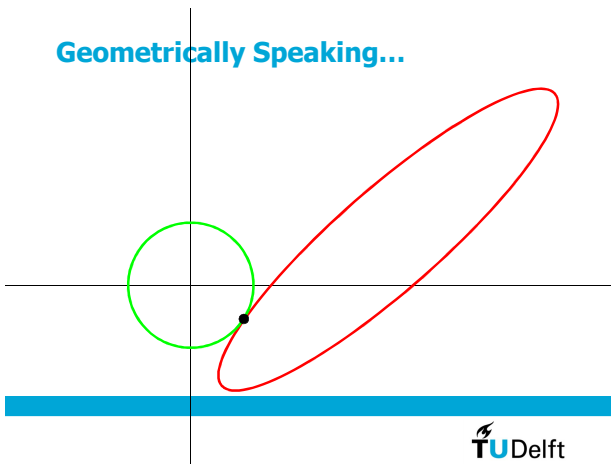
Short Intermezzo?

- What is the shape of these functions?

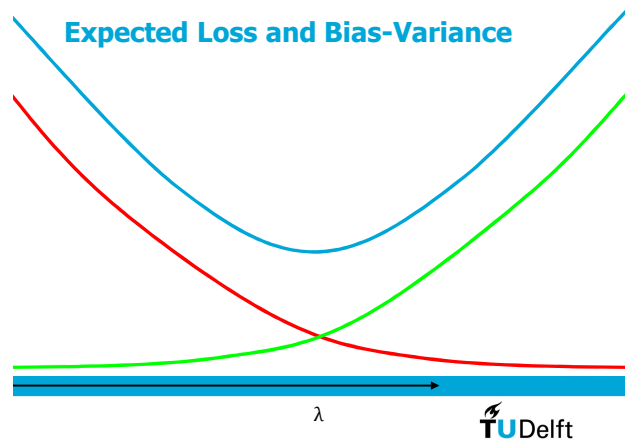
$$\begin{aligned} \sum_{i=1}^N (f(x_i, w) - y_i)^2 + \lambda \|w\|^2 \\ \sum_{i=1}^N (f(x_i, w) - y_i)^2 \\ \|w\|^2 \end{aligned}$$



Geometrically Speaking...



Expected Loss and Bias-Variance



Regularized Risk

- General approach to regularization

$$\min_w \sum_{i=1}^N \ell(f(x_i, w), y_i) + R(f)$$

- Many learning problems in PR and ML can be [and are in fact] formulated in this way
- Different considerations give different R
- Various links : MAP, MDL, SRM, etc.



Introducing Sparsity

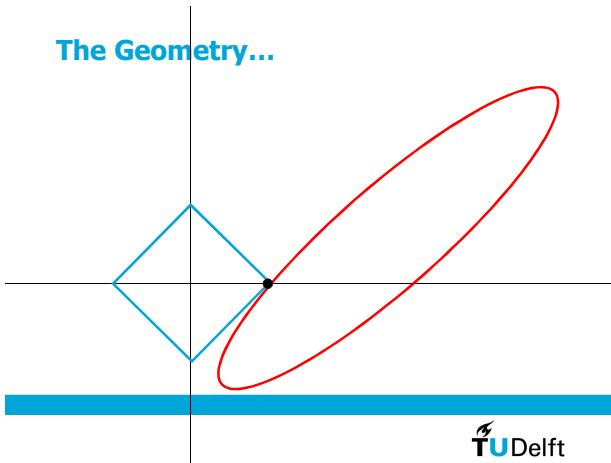
- For a change, let us consider

$$\begin{aligned} \min_w \sum_{i=1}^N (f(x_i, w) - y_i)^2 \\ \text{s. t. } \|w\|_1 \leq \tau \end{aligned}$$

- Q : what is the shape of $\|w\|_1$?
- Q : what is the effect of this change of norm?



The Geometry...



Again the Equivalent View...

- Include sparsifying norm as an additive term

$$\min_w \sum_{i=1}^N (f(x_i, w) - y_i)^2 + \lambda \|w\|_1$$

- Matlab "demo" ...?



Final Remarks

- Sparsity by regularization due to Tibshirani
 - Least absolute shrinkage and selection operator or lasso
 - Performs feature selection
 - Compare to feature forward selection etc.!
- Regularization framework also used for classification...

