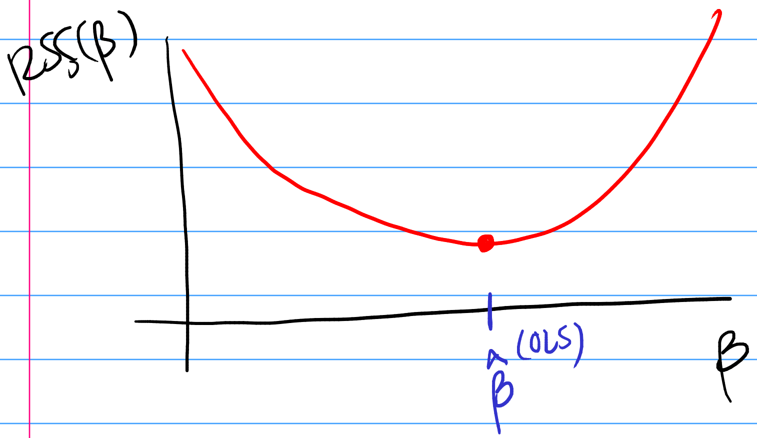
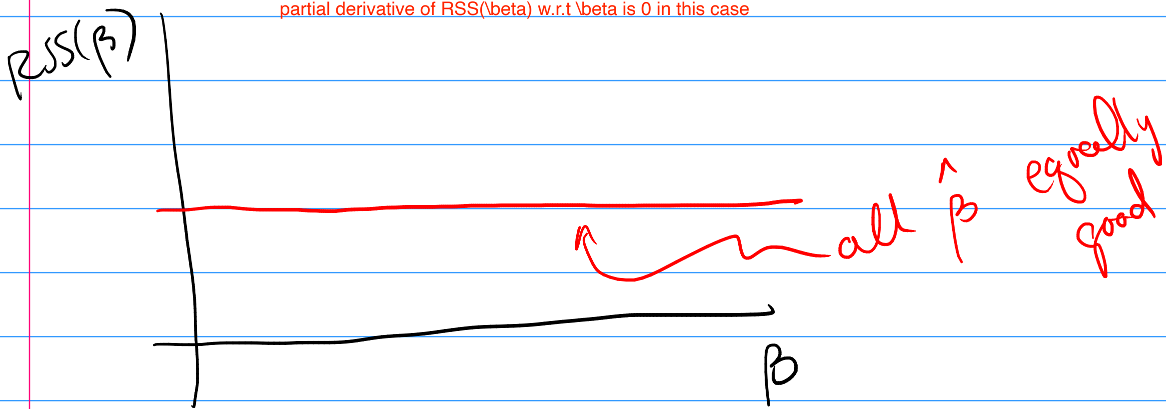
Lecture 4:

1) X^TX is invertible

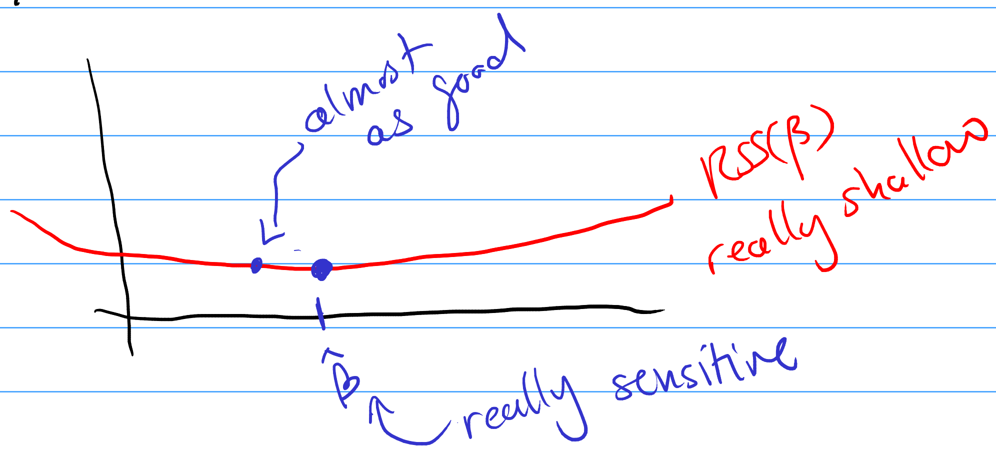


2) X^TX not invertible

Check that \partial RSS(\beta)/ \partial \beta =0 , i.e., the partial derivative of RSS(\beta) w.r.t \beta is 0 in this case



3) X^TX close to not invertible

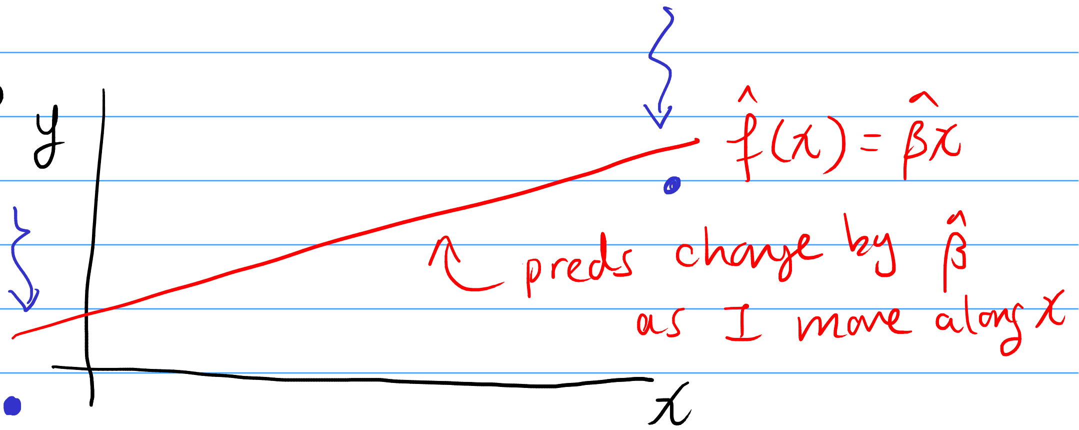


KNN Regression (k-nearest neighbors regression)

Recall for LR: we have a really strong global assumption abot f

$$f(\underset{\sim}{x}) = \underline{x}^T \beta$$

e.g. in 1D



Furthermore: traing data affects the fit far away

Benefit: strong global assumption make $\hat{f}$ practical to find

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kNN makes a weaker local assumption that vales of $\hat{f}(\underset{\sim}{x})$ only depend on nearby training points.

k = integer that determines how many "nearby" traing points we consider

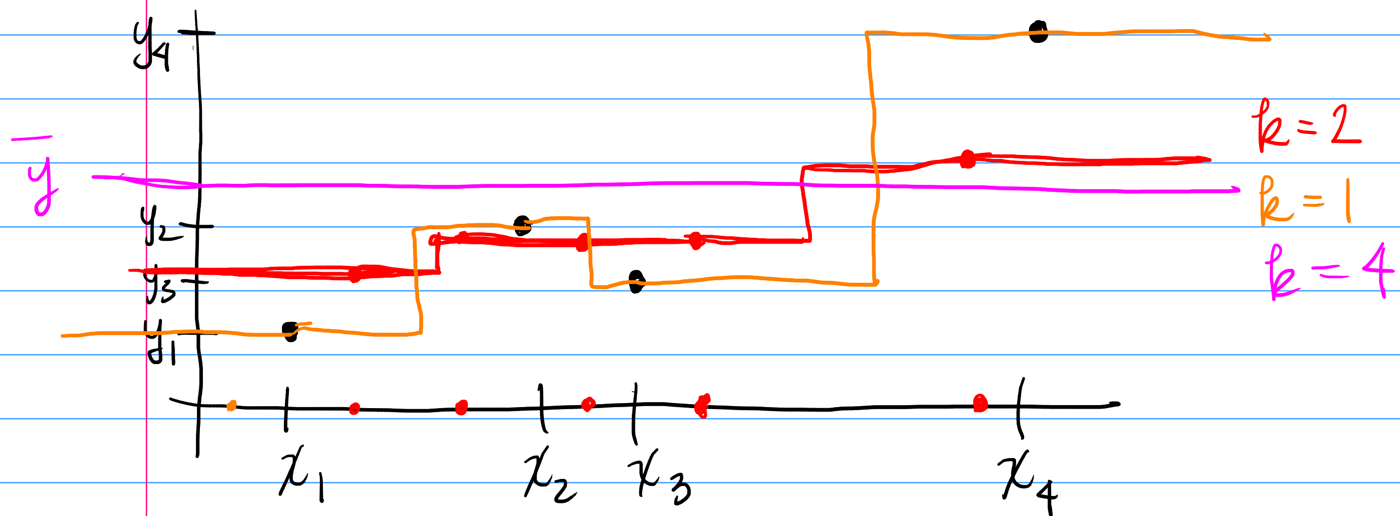
Given traing data $\{(\underset{\sim}{x}_n, y_n)\}_{n=1}^{N}$

kNN fits $\hat{f}$ as

$$\hat{f}(\underset{\sim}{x}) = \frac{1}{k} \sum_{n \in N_k(\underset{\sim}{x})} y_n$$ = avg. y_n over k nearest neighbors to $\underset{\sim}{x}$

$N_k(\underset{\sim}{x})$ = k neighborhood of $\underset{\sim}{x}$
= indices of k nearest training pts to $\underset{\sim}{x}$

for numeric typically use euclidean distance



What happens as we change k?

general rule: k controls the flexibility of the method

↳ how complicated of a function $\hat{f}$ is

Small k → very flexible method
e.g. $k=1$ interpolates data

large k → very inflexible method
e.g. $k=N$ I just predict $\bar{y}$ \hat y

Comparison w/ OLS:

OLS reduces $\mathcal{F}$ to a p-dim'l space.

kNN reduces $\mathcal{F}$ to a N/k dim'l space.

as k ↑ I reduce the dim of the space

(VC dimension Vapnik-Chervonensk)

converse: k ↓ I increase the dim

VC dimension is beyond the scope of the class