# CS724: Topics in Algorithms Least Square Approximations Slide Set 11 

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(1) Linear Regression
(2) The Least Square Approximation and QR Decomposition

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CS724: Topics in Algorithms Least Square

The least square method is used in data mining as a method of estimating the parameters of a model by adopting the values that minimize the sum of the squared differences between the predicted and the observed values of data.
This estimation process is also known as regression, and several types of regression exist depending on the nature of the assumed model of dependency between the predicted and the observed data.

The aim of linear regression is to explore the existence of a linear relationship between the outcome of an experiment and values of variables that are measured during the experiment. Experimental data often is presented as a data sample matrix $X \in \mathbb{R}^{m \times n}$, where $m$ is the number of experiments and $n$ is the number of variables measured. The results of the experiments are the components of a vector

$$
\boldsymbol{b}=\left(\begin{array}{c}
b_{1} \\
\vdots \\
b_{m}
\end{array}\right)
$$

Linear regression amounts to determining $r \in \mathbb{R}^{n}$ such that $X \boldsymbol{r}=\boldsymbol{b}$. Knowing the components of $\boldsymbol{r}$ allows us to express the value of the result as a linear combination of the values of the variables. Unfortunately, since $m$ is usually much larger than $n$, this system is overdetermined and, in general, is inconsistent.

The columns $\boldsymbol{v}_{1}, \ldots, \boldsymbol{v}_{n}$ of the matrix $X$ are referred to as the regressors; the linear combination $r_{1} \boldsymbol{v}_{1}+\cdots+r_{n} \boldsymbol{v}_{n}$ is the regression of $\boldsymbol{b}$ onto the regressors $\boldsymbol{v}_{1}, \ldots, \boldsymbol{v}_{n}$.

Let us study the data set that represent (using the function plot of MATLAB ), the number of calories consumed by a person per day vs. the gross national product per person in European countries.

| ccode | gdp | cal | ccode | gdp | cal |
| :--- | ---: | ---: | :--- | :--- | ---: |
| 'AL' | 0.74 | 2824.00 | 'IT' | 3.07 | 3685.00 |
| 'AT' | 4.03 | 3651.00 | 'LV' | 1.43 | 3029.00 |
| 'BY' | 1.34 | 2895.00 | 'LT' | 1.59 | 3397.00 |
| 'BE' | 3.79 | 3698.00 | 'LU' | 8.18 | 3778.00 |
| 'BA' | 0.66 | 2950.00 | 'MK' | 0.94 | 2881.00 |
| 'BG' | 1.28 | 2813.00 | 'MT' | 2.51 | 3535.00 |
| 'HR' | 1.75 | 2937.00 | 'MD' | 0.25 | 2841.00 |
| 'CY' | 1.21 | 3208.00 | 'NL' | 4.05 | 3240.00 |
| 'CZ' | 2.56 | 3346.00 | 'NO' | 5.91 | 3448.00 |
| 'DK' | 3.67 | 3391.00 | 'PL' | 1.88 | 3375.00 |
| 'EE' | 1.90 | 3086.00 | 'PT' | 2.30 | 3593.00 |
| 'FI' | 3.53 | 3195.00 | 'RO' | 1.15 | 3474.00 |
| 'FR' | 3.33 | 3602.00 | 'RU' | 1.59 | 3100.00 |
| 'GE' | 0.48 | 2475.00 | 'YU' | 1.10 | 2689.00 |
| 'DE' | 3.59 | 3491.00 | 'SK' | 2.22 | 2825.00 |
| 'GR' | 3.02 | 3694.00 | 'SI' | 2.84 | 3271.00 |
| 'HU' | 1.90 | 3420.00 | 'ES' | 2.95 | 3329.00 |
| 'IS' | 3.67 | 3279.00 | 'CH' | 4.29 | 3400.00 |
| 'IE' | 3.76 | 3685.00 |  |  |  |

## This data is represented below:



We seek to approximate the calorie intake as a linear function of the gdp of the form

$$
\mathrm{cal}=r_{1}+r_{2} \mathrm{gdp}
$$

This amounts to solving a linear system that consists of 37 equations and two unknowns:

$$
\begin{aligned}
r_{1}+0.74 r_{2} & =2824 \\
& \vdots \\
r_{1}+4.29 r_{2} & =3400
\end{aligned}
$$

and, clearly such a system is inconsistent.

If the linear system $X \boldsymbol{r}=\boldsymbol{b}$ has no solution, the "next best thing" is to find a vector $\boldsymbol{c} \in \mathbb{R}^{n}$ such that $\|X \boldsymbol{c}-\boldsymbol{b}\|_{2} \leq\|X \boldsymbol{w}-\boldsymbol{b}\|_{2}$ for every $\boldsymbol{w} \in \mathbb{R}^{n}$, an approach known as the least square method. We will refer to the triple $(X, \boldsymbol{r}, \boldsymbol{b})$ as an instance of the least square problem. Note that $X r \in \operatorname{range}(X)$ for any $r \in \mathbb{R}^{n}$. Thus, solving this problem amounts to finding a vector $X r$ in the subspace range $(X)$ such that $X r$ is as close to $\boldsymbol{b}$ as possible.

Let $X \in \mathbb{R}^{m \times n}$ be a full-rank matrix such that $m>n$, so $\operatorname{rank}(X)=n$. The symmetric square matrix $X^{\prime} X \in \mathbb{R}^{n \times n}$ has the same rank $n$ as the matrix $X$. Therefore, the system $\left(X^{\prime} X\right) \boldsymbol{r}=X^{\prime} \boldsymbol{b}$ a unique solution $\boldsymbol{s}$.
Moreover, $X^{\prime} X$ is positive definite because $\boldsymbol{r}^{\prime} X^{\prime} X \boldsymbol{r}=(X \boldsymbol{r})^{\prime} X \boldsymbol{r}=\|X \boldsymbol{r}\|_{2}^{2}>0$ for $\boldsymbol{r} \neq \mathbf{0}$.

## Theorem

Let $X \in \mathbb{R}^{m \times n}$ be a full-rank matrix such that $m>n$ and let $\boldsymbol{b} \in \mathbb{R}^{m}$. The unique solution of the system $\left(X^{\prime} X\right) \mathbf{r}=X^{\prime} \mathbf{b}$ equals the projection of the vector $\boldsymbol{b}$ on the subspace range $(X)$.

## Proof

The $n$ columns of the matrix $X=\left(\boldsymbol{v}_{1} \cdots \boldsymbol{v}_{n}\right)$ constitute a basis of the subspace range $(X)$. Therefore, we seek the projection $\boldsymbol{c}$ of $\boldsymbol{b}$ on range $(X)$ as a linear combination $\boldsymbol{c}=\boldsymbol{X t}$, which allows us to reduce this problem to a minimization of the function

$$
\begin{aligned}
f(\boldsymbol{t}) & =\|X \boldsymbol{t}-\boldsymbol{b}\|_{2}^{2} \\
& =(X \boldsymbol{t}-\boldsymbol{b})^{\prime}(X \boldsymbol{t}-\boldsymbol{b})=\left(\boldsymbol{t}^{\prime} X^{\prime}-\boldsymbol{b}^{\prime}\right)(X \boldsymbol{t}-\boldsymbol{b}) \\
& =\boldsymbol{t}^{\prime} X^{\prime} X \boldsymbol{t}-\boldsymbol{b}^{\prime} X \boldsymbol{t}-\boldsymbol{t}^{\prime} X^{\prime} \boldsymbol{b}+\boldsymbol{b}^{\prime} \boldsymbol{b} .
\end{aligned}
$$

The necessary condition for the minimum is

$$
(\nabla f)(\boldsymbol{t})=2 X^{\prime} X \boldsymbol{t}-2 X^{\prime} \boldsymbol{b}=0
$$

which implies $X^{\prime} X \boldsymbol{t}=X^{\prime} \mathbf{b}$.

The linear system $\left(X^{\prime} X\right) \boldsymbol{t}=X^{\prime} \boldsymbol{b}$ is known as the system of normal equations of $X$ and $\boldsymbol{b}$.

## Example

We augment the data sample matrix by a column that consists of 1 s to accommodate a constant term $r_{1}$; thus, we work with the data sample matrix $X \in \mathbb{R}^{37 \times 2}$ given by

$$
X=\left(\begin{array}{cc}
1 & 0.74 \\
\vdots & \vdots \\
1 & 4.29
\end{array}\right)
$$

whose second column consists of the countries' gross domestic products in $\$ 10 \mathrm{~K}$ units. The matrix $C=X^{\prime} X$ is

$$
C=\left(\begin{array}{cc}
37.0000 & 94.4600 \\
94.4600 & 333.6592
\end{array}\right) .
$$

## Example cont'd

## Example

Solving the normal system using the MATLAB statement $\boldsymbol{r}=C \backslash\left(X^{\prime} * b\right)$ yields

$$
r=\binom{2894.2}{142.3}
$$

so the regression line is cal $=142.3 * \mathrm{gdp}+2894.2$, shown in next:


Suppose now that $X \in \mathbb{R}^{m \times n}$ has rank $k$, where $k<\min \{m, n\}$, and $U \in \mathbb{R}^{m \times m}, V \in \mathbb{R}^{n \times n}$ are orthonormal matrices such that $X$ can be factored as $X=U M V^{\prime}$, where

$$
M=\left(\begin{array}{cc}
R & O_{k, n-k} \\
O_{m-k, k} & O_{m-k, n-k}
\end{array}\right) \in \mathbb{R}^{m \times n},
$$

$R \in \mathbb{R}^{k \times k}$, and $\operatorname{rank}(R)=k$.
For $\boldsymbol{b} \in \mathbb{R}^{m}$ define $\boldsymbol{c}=U^{\prime} \boldsymbol{b} \in \mathbb{R}^{m}$ and let $\boldsymbol{c}=\binom{\boldsymbol{c}_{1}}{\boldsymbol{c}_{2}}$, where $\boldsymbol{c}_{1} \in \mathbb{R}^{k}$ and $\boldsymbol{c}_{2} \in \mathbb{R}^{m-k}$. Since $\operatorname{rank}(R)=k$, the linear system $R \boldsymbol{z}=\boldsymbol{c}_{1}$ has a unique solution $\boldsymbol{z}_{1}$.

Theorem
All vectors $\boldsymbol{r}$ that minimize $\|X \boldsymbol{r}-\boldsymbol{b}\|_{2}$ have the form

$$
\boldsymbol{r}=V\binom{\boldsymbol{z}}{\boldsymbol{w}}
$$

for an arbitrary $\boldsymbol{w}$.

## Proof

We have

$$
\begin{aligned}
\|X \boldsymbol{r}-\boldsymbol{b}\|_{2}^{2} & =\left\|U M V^{\prime} \boldsymbol{r}-U U^{\prime} \boldsymbol{b}\right\|_{2}^{2} \\
& =\left\|U\left(M V^{\prime} \boldsymbol{r}-U^{\prime} \boldsymbol{b}\right)\right\|_{2}^{2}=\left\|M V^{\prime} \boldsymbol{r}-U^{\prime} \boldsymbol{b}\right\|_{2}^{2}
\end{aligned}
$$

(because multiplication by an orthonormal matrix is norm-preserving)

$$
\begin{aligned}
& =\left\|M V^{\prime} \boldsymbol{r}-\boldsymbol{c}\right\|_{2}^{2}=\|M \boldsymbol{y}-\boldsymbol{c}\|_{2}^{2} \\
& =\left\|R \boldsymbol{z}-\boldsymbol{c}_{1}\right\|_{2}^{2}+\left\|\boldsymbol{c}_{2}\right\|_{2}^{2},
\end{aligned}
$$

where $\boldsymbol{z}$ consists of the first $r$ components of $\boldsymbol{y}$. This shows that the minimal value of $\|X \boldsymbol{r}-\boldsymbol{b}\|_{2}^{2}$ is achieved by the solution of the system $R \boldsymbol{z}=\boldsymbol{c}_{1}$ and is equal to $\left\|\boldsymbol{c}_{2}\right\|_{2}^{2}$. Therefore, the vectors $\boldsymbol{r}$ that minimize $\|X \boldsymbol{r}-\boldsymbol{b}\|_{2}^{2}$ have the form $\binom{\boldsymbol{z}}{\boldsymbol{w}}$ for an arbitrary $\boldsymbol{w} \in \mathbb{R}^{n-r}$.

Instead of the Euclidean norm we can use the $\|\cdot\|_{\infty}$. Note that we have $t=\|X \boldsymbol{r}-\boldsymbol{b}\|_{\infty}$ if and only if $-t \mathbf{1} \leq X \boldsymbol{r}-\boldsymbol{b} \leq t \mathbf{1}$, so finding $\boldsymbol{r}$ that minimizes $\|\cdot\|_{\infty}$ amounts to solving a linear programming problem: minimize $t$ subjected to the restrictions $-t \mathbf{1} \leq X \boldsymbol{r}-\boldsymbol{b} \leq t \mathbf{1}$. Similarly, we can use the norm $\|\cdot\|_{p}$. If $\boldsymbol{y}=X \boldsymbol{r}-\boldsymbol{b}$, then we need to minimize $\|\boldsymbol{y}\|_{p}^{p}=\left|y_{1}\right|^{p}+\cdots+\left|y_{m}\right|^{p}$, subjected to the restrictions $-\boldsymbol{y} \leq A \boldsymbol{r}-\boldsymbol{b} \leq \boldsymbol{y}$.

Solving the system of normal equation presents numeric difficulties because the condition number of the matrix $X^{\prime} X$ is the square of the condition number of $X$. An alternative approach to finding $r \in \mathbb{R}^{n}$ that minimizes $f(\boldsymbol{u})=\|X \boldsymbol{u}-\boldsymbol{b}\|_{2}^{2}$ is to use a full QR decomposition of the matrix $X$, where $X \in \mathbb{R}^{m \times n}$ is a full-rank matrix and $m>n$.

Suppose that

$$
X=Q\binom{R}{O_{m-n, n}}
$$

where $Q \in \mathbb{R}^{m \times m}$ is an orthonormal matrix and $R \in \mathbb{R}^{n \times n}$ is an upper triangular matrix such that

$$
\binom{R}{O_{m-n, n}} \in \mathbb{R}^{m \times n}
$$

We have

$$
\begin{aligned}
X \boldsymbol{u}-\boldsymbol{b} & =Q\binom{R}{O_{m-n, n}} \boldsymbol{u}-\boldsymbol{b} \\
& =Q\binom{R}{O_{m-n, n}} \boldsymbol{u}-Q Q^{\prime} \boldsymbol{b}
\end{aligned}
$$

(because $Q$ is orthonormal and therefore $Q Q^{\prime}=I_{m}$ )

$$
=Q\left(\binom{R}{O_{m-n, n}} \boldsymbol{u}-Q^{\prime} \boldsymbol{b}\right) .
$$

multiplication by an orthogonal matrix preserves the Euclidean norm of vectors. Thus,

$$
\|X \boldsymbol{u}-\boldsymbol{b}\|_{2}^{2}=\left\|\binom{R}{O_{m-n, n}} \boldsymbol{u}-Q^{\prime} \boldsymbol{b}\right\|_{2}^{2}
$$

If we write $Q=\left(L_{1} L_{2}\right)$, where $L_{1} \in \mathbb{R}^{m \times n}$ and $L_{2} \in \mathbb{R}^{m \times(m-n)}$, then

$$
\begin{aligned}
\|X \boldsymbol{u}-\boldsymbol{b}\|_{2}^{2} & =\left\|\binom{R}{O_{m-n, n}} \boldsymbol{u}-\binom{L_{1}^{\prime} \boldsymbol{b}}{L_{2}^{\prime} \boldsymbol{b}}\right\|_{2}^{2} \\
& =\left\|\binom{R \boldsymbol{u}-L_{1}^{\prime} \boldsymbol{b}}{-L_{2}^{\prime} \boldsymbol{b}}\right\|_{2}^{2} \\
& =\left\|R \boldsymbol{u}-L_{1}^{\prime} \boldsymbol{b}\right\|_{2}^{2}+\left\|L_{2}^{\prime} \boldsymbol{b}\right\|_{2}^{2} .
\end{aligned}
$$

Observe that the system $R \boldsymbol{u}=L_{1}^{\prime} \boldsymbol{b}$ can be solved and its solution minimizes $\|X \boldsymbol{u}-\boldsymbol{b}\|_{2}$.

