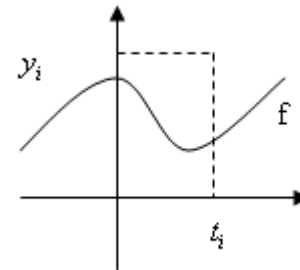


# Vandermonde Matrix / Circulant Matrix

P: Given  $\{t_i, y_i | i = 1 \sim m\}$  find a function  $f$  consists with  $n$  parameters ( $m \geq n$ ) that gives

$$\min_x \sum_{i=1}^m (y_i - f(t_i, x))^2$$



$$\Rightarrow \nabla_x \left( \sum_{i=1}^m (y_i - f(t_i, x))^2 \right) = 0$$

$$\Rightarrow \sum_{i=1}^m 2(y_i - f(t_i, x))^2 \nabla_x f(t_i, x) = 0 \quad \text{-(VI)}$$

Assuming  $f$  depends on  $x$  linearly,  $P$  is called a linear problem.

In this case, we consider

$$f(t, x) = \sum_{j=1}^n x_j \phi_j(t)$$

$$(VI) \Rightarrow \sum_{j=1}^n \left( y_i - \sum_{j=1}^n x_j \phi_j(t_i) \right) \cdot \begin{pmatrix} \phi_1(t_i) \\ \vdots \\ \phi_n(t_i) \end{pmatrix} = 0 \Rightarrow \begin{cases} \sum_{j=1}^n \sum_{i=1}^m x_j \phi_j(t_i) \phi_1(t_i) - \sum_{i=1}^m y_i \phi_1(t_i) = 0 \\ \vdots \\ \sum_{j=1}^n \sum_{i=1}^m x_j \phi_j(t_i) \phi_n(t_i) - \sum_{i=1}^m y_i \phi_n(t_i) = 0 \end{cases}$$

$$\Rightarrow \Phi_{n \times m}^T \begin{bmatrix} \Phi_{m \times n} \vec{x} - \vec{y} \end{bmatrix}_{\substack{n \times 1 \\ m \times 1}} = 0 \quad \text{-----} \quad (++)$$

$$\text{here } \vec{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}, \vec{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_m \end{bmatrix}, \Phi = \begin{bmatrix} \phi_1(t_1) & \cdots & \phi_n(t_1) \\ \phi_1(t_2) & & \phi_n(t_2) \\ \vdots & & \vdots \\ \phi_1(t_m) & \cdots & \phi_n(t_m) \end{bmatrix}_{m \times n}$$

(1) When  $\phi_1 = 1$ ,  $\phi_2 = t$ ,  $\phi_3 = t^2$ ,  $\dots$   $\phi_n = t^{n-1}$ , one has

$$\Phi = \begin{bmatrix} 1 & t_1 & t_1^2 & \cdots & t_1^{n-1} \\ 1 & t_2 & t_2^2 & \cdots & t_2^{n-1} \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & t_m & t_m^2 & \cdots & t_m^{n-1} \end{bmatrix}$$

The matrix  $\Phi$  is called the Vandermonde matrix.

It can be shown,  $\Phi$  is nonsingular when  $m = n$ .

Solving the equation  $\Phi x = y$  is equivalent to find the

polynomial  $p(t) = \sum_{i=0}^{n-1} x_i t^i$  with degree  $n-1$  such that

$$p(t_1) = y_1 \cdots p(t_n) = y_n$$

It is well known this polynomial exists and unique.

It is called the Lagrange polynomial.

Now, how to solve  $(++)$  efficiently?

Find  $p(x) = \sum_{k=0}^{n-1} a_k x^k$  that satisfy  $p(x_k) = y_k, k = 0 \sim n-1$

Consider the Newton representation of the interpolating polynomial  $p$ .

$$p(x) = C_0 + (x - x_0) \left\{ C_1 + (x - x_1) \left\{ C_2 + (x - x_2) \left\{ C_3 + \cdots \left\{ C_{n-2} + (x - x_{n-2}) C_{n-1} \right\} \cdots \right\} \right\} \right\}$$

$$= \sum_{k=0}^{n-1} C_k \prod_{i=0}^{k-1} (x - x_i)$$

$$\Rightarrow C_0 = p(x_0) = y_0$$

$$C_1 = \frac{p(x_1) - C_0}{x_1 - x_0} = \frac{y_1 - y_0}{x_1 - x_0}$$

$$C_2 = \frac{p(x_2) - C_0 - (x_2 - x_0)C_1}{x_2 - x_1}$$

$\vdots$

$$C_{n-1} = \frac{p(x_{n-1}) - \sum_{k=0}^{n-2} C_k \prod_{i=0}^{k-1} (x_{n-1} - x_i)}{\prod_{i=0}^{n-1} (x_{n-1} - x_i)}$$

Algorithm 1

$$\Rightarrow \left\{ \begin{array}{l} C(0:n-1) = [y_0, \cdots, y_{n-1}] \\ \text{For } k = 0:n-2 \\ \quad \text{For } i = n-1 \text{ to } k+1 \\ \qquad C_i = \frac{C_i - C_{i-1}}{x_i - x_{i-k-1}} \\ \quad \text{end} \\ \text{end} \end{array} \right.$$

Computing  $C_0, C_1 \sim C_{n-1}$  costs  $O(n^2)$

Next, we generate  $a_k, k = 0 \sim n-1$ , from  $C_0, C_1 \sim C_{n-1}$

Consider  $p_{n-1}(x), p_{n-2}(x), \dots, p_0(x)$  generated by

$$p_{n-1}(x) = C_{n-1}, p_k(x) = C_k + (x - x_k) p_{k+1}, k = n-2 \sim 0.$$

$$\text{let } p_k(x) = a_k^{(k)} + a_{k+1}^{(k)} x + \dots + a_{n-1}^{(k)} x^{n-k-1}$$

$$= C_k + (x - x_k) \left[ a_{k+1}^{(k+1)} + a_{k+2}^{(k+1)} x + \dots + a_{n-1}^{(k+1)} x^{n-k-2} \right]$$

$$\Rightarrow a_k^{(k)} = C_k - x_k a_{k+1}^{(k+1)}, a_{k+1}^{(k)} = a_{k+1}^{(k+1)} - x_k a_{k+2}^{(k+1)}, a_{k+2}^{(k)} = a_{k+2}^{(k+1)} - x_k a_{k+3}^{(k+1)}, \dots$$

$$\Rightarrow (*) \left\{ \begin{array}{l} a_k^{(k)} = C_k - x_k a_{k+1}^{(k+1)} \\ \text{For } i = k+1: n-2 \\ a_i^{(k)} = a_i^{(k+1)} - x_k a_{i+1}^{(k+1)} \\ \text{end} \\ a_{n-1}^{(k)} = a_{n-1}^{(k+1)} \end{array} \right.$$

$\Rightarrow$  Excuting (\*) from n-2 to 0 gives the coefficients

$$a_0^{(0)}, a_1^{(0)}, a_2^{(0)}, \dots, a_{n-1}^{(0)} = a_0, a_1, \dots, a_{n-1}$$

The above process can be written as following:

Algorithm 2:

```
a(0: n-1) = C(0: n-1)
For k = n-2 to 0
  For i = k to n-2
     $a_i = a_i - x_k a_{i+1}$ 
  end
end
```

} operation counts  $O(n^2)$

Remark: (1) Solving the Vandermonde Matrix costs  $O(n^2)$  operations.

(2) Algorithm 1 and 2 generate accurate solution even when the matrix is ill-conditioned.

(2) Consider  $\phi_j(t) = w_{j-1} = \left( e^{-i\frac{2\pi t}{n}} \right)^{j-1}$ ,  $j = 1 \sim n$ , where  $w$

is the  $j$ th root of  $x^n = 1$  ( $w_j^n = 1$ ) and  $t_i = i$ ,  $i = 1 \sim n$

$$\Phi_N = \begin{bmatrix} \phi_1(0) & \phi_2(0) & \cdots & \phi_n(0) \\ \phi_1(1) & \phi_2(1) & \cdots & \phi_n(1) \\ \vdots & \vdots & \vdots & \vdots \\ \phi_1(n-1) & \phi_2(n-1) & \cdots & \phi_n(n-1) \end{bmatrix} \left( \begin{array}{l} \text{let } w = e^{-i\frac{2\pi}{n}}, w_1 = w, w_2 = w^2, \dots \\ w^{\frac{n}{2}} = -1, \dots, w_{n-1} = w^{n-1}, w^n = 1 \end{array} \right)$$

$$= \begin{bmatrix} 1 & w_1^0 & w_2^0 & \cdots & w_{n-1}^0 \\ 1 & w_1 & w_2 & \cdots & w_{n-1} \\ 1 & w_1^2 & w_2^2 & \cdots & w_{n-1}^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & w_1^{n-1} & w_2^{n-1} & \cdots & w_{n-1}^{n-1} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & \cdots & 1 \\ 1 & w & w^2 & \cdots & w^{n-1} \\ 1 & w^2 & w^4 & \cdots & w^{2(n-1)} \\ 1 & w^3 & w^6 & \cdots & w^{3(n-1)} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & w^{n-2} & w^{2(n-2)} & \cdots & w^{(n-2)(n-1)} \\ 1 & w^{n-1} & w^{2(n-1)} & \cdots & w^{(n-1)^2} \end{bmatrix} \begin{array}{l} 0 \\ 1 \\ 2 \\ \vdots \\ \vdots \\ \vdots \\ n-1 \end{array}$$

To solve  $\Phi_N x = y$  is equivalent to find the coefficients of the fourier expansion of  $y$





$$\text{let } \Omega_{\frac{N}{2}} = \begin{bmatrix} 1 & & & & & \\ & w & & & & \\ & & w^2 & & & \\ & & & \ddots & & \\ & 0 & & & \ddots & \\ & & & & & w^{\frac{N}{2}-1} \end{bmatrix}, \Phi_{\frac{N}{2}} = \begin{bmatrix} 1 & 1 & \dots & 1 \\ w^2 & w^4 & \dots & w^{n-2} \\ w^4 & w^8 & \dots & w^{n-4} \\ \vdots & \vdots & & \vdots \\ w^{n-2} & w^{n-4} & \dots & w^2 \end{bmatrix}$$

$$(**) \underset{(B)}{=} \left[ \begin{array}{c|cc} \Phi_{\frac{N}{2}} & \Omega_{\frac{N}{2}} \Phi_{\frac{N}{2}} \\ \hline \Phi_{\frac{N}{2}} & -\Omega_{\frac{N}{2}} \Phi_{\frac{N}{2}} \end{array} \right] \xrightarrow[\text{(A)\&(B)}]{\text{repeat}} \Phi_{\frac{N}{2}} = \left[ \begin{array}{c|cc} \Phi_{\frac{N}{4}} & \Omega_{\frac{N}{4}} \Phi_{\frac{N}{4}} \\ \hline \Phi_{\frac{N}{4}} & -\Omega_{\frac{N}{4}} \Phi_{\frac{N}{4}} \end{array} \right], \Omega_{\frac{N}{4}} = \begin{bmatrix} 1 & & & & & \\ & w^2 & & & & \\ & & w^4 & & & \\ & & & \ddots & & \\ & 0 & & & \ddots & \\ & & & & & w^{\frac{N}{2}-2} \end{bmatrix}$$

$\Rightarrow$  keep doing until  $\dim(\Phi) = 1$ .

The above process is the matrix version of the well known FFT (Fast Fourier Transformation) procedure.

exercise:

Show that (1)  $\frac{1}{N} \Phi^* \Phi = I$  (2)  $\Phi$  is nonsingular.

To solve  $\Phi^* (\Phi x - y) = 0 \equiv$  To solve  $\Phi x = y$

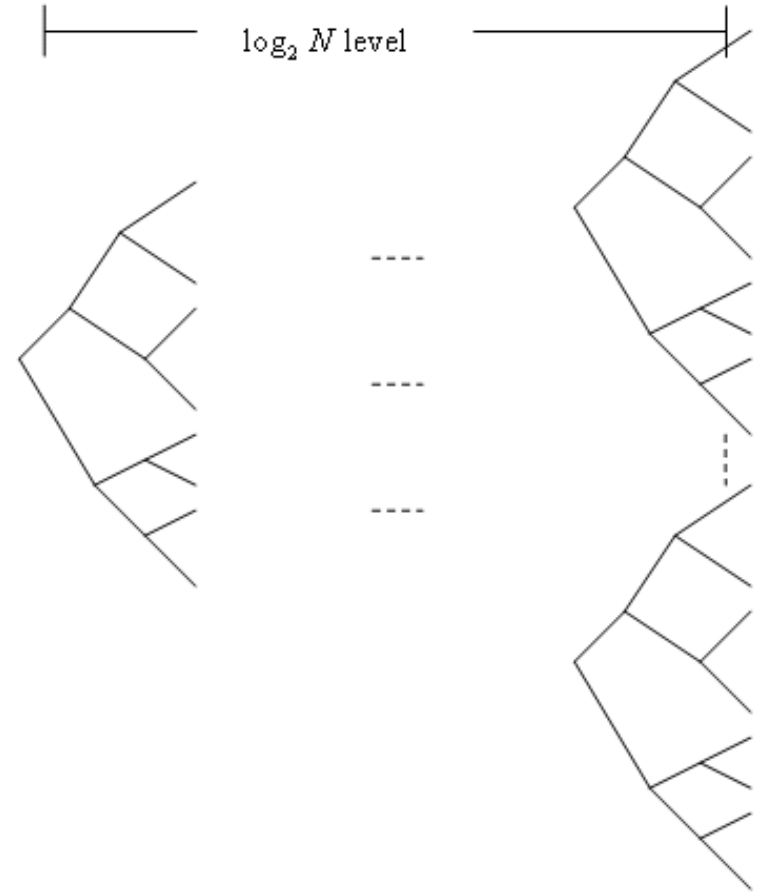
We only needs to apply  $\frac{1}{N} \Phi^*$  to the equation.

Moreover,  $x = \frac{1}{N} \Phi^* y$  can be computed extremely fast due to the above recursive relation.

Remark: In fact, the algorithm can be implemented in  $O(n \log n)$  operations.

$$\text{By, } \Phi_k x^{(k)} = \begin{bmatrix} \Phi_{\frac{k}{2}} x_{\text{even}}^{(k)} + \Omega_{\frac{k}{2}} \Phi_{\frac{k}{2}} x_{\text{odd}}^{(k)} \\ \Phi_{\frac{k}{2}} x_{\text{even}}^{(k)} - \Omega_{\frac{k}{2}} \Phi_{\frac{k}{2}} x_{\text{odd}}^{(k)} \end{bmatrix},$$

$\Phi_N x$  can now be computed recursively starting from computing  $\Phi_1 x_i, i = 0 \dots n-1$ .



Total cost for FFT

$$= 3 \cdot 2^{n-1} \cdot \frac{N}{2^{N-1}} + \dots + \left( 3 \cdot 2^2 \frac{N}{2^2} \right) (3 \cdot 2) \frac{N}{2} + N$$

$$< 3N \log_2 N$$

# Circulant Matrix :

$$C(v) = \begin{bmatrix} v_0 & v_{n-1} & v_{n-2} & \cdots & v_1 \\ v_1 & v_0 & v_{n-1} & \cdots & v_2 \\ \vdots & & \ddots & \ddots & \vdots \\ v_{n-2} & \cdots & \cdots & v_0 & v_{n-1} \\ v_{n-1} & \cdots & \cdots & v_1 & v_0 \end{bmatrix} \text{ is called circulant matrix.}$$

Given a vector  $x \in \mathbb{R}^n$ , the product  $C(v) \cdot x$  is called the convolution of  $x$  with  $v$  and the product of  $C(v)^{-1} \cdot y$  is called the deconvolution of  $y$  from  $v$ .

The matrix is formed by  $C(v) = [v, sv, s^2v, \dots, s^{n-1}v]$  where

$$S = \begin{bmatrix} 0 & 0 & \cdots & 0 & 1 \\ 1 & 0 & \cdots & \cdots & 0 \\ & 1 & \ddots & 0 & \vdots \\ & & \ddots & \ddots & \vdots \\ 0 & & & 1 & 0 \end{bmatrix} \text{ is called a "downshifted " matrix}$$

First let's show characteristic polynomial of  $C(v)$  has  $n$  roots.

Prove that the characteristic root of the circulant  $C(v)$  is

$$y = v_1 r^{n-1} + v_2 r^{n-2} + \cdots + v_{n-1} r + v_0 \quad \text{where } r^n = 1$$

let  $y_1 = v_1 r^{n-1} + v_2 r^{n-2} + \cdots + v_{n-1} r + v_0$ .

We have  $ry_1 = v_2 r^{n-1} + \cdots + v_{n-1} r^2 + v_0 r + v_1$

$$r^2 y_1 = v_3 r^{n-1} + \cdots + v_{n-1} r^3 + v_0 r^2 + v_1 r + v_2$$

$\vdots$

$$r^{n-1} y_1 = v_0 r^{n-1} + v_1 r^{n-2} + \cdots + v_{n-2} r + v_{n-1}$$

$$\Rightarrow \begin{bmatrix} v_0 & v_{n-1} & \cdots & v_2 & v_1 \\ v_1 & v_0 & \cdots & v_3 & v_2 \\ & \ddots & \ddots & \vdots & \vdots \\ & & \ddots & v_0 & v_{n-1} \\ v_{n-1} & v_{n-2} & \cdots & v_1 & v_0 \end{bmatrix} \begin{bmatrix} 1 \\ r \\ r^2 \\ \vdots \\ r^{n-1} \end{bmatrix} = y_1 \begin{bmatrix} 1 \\ r \\ r^2 \\ \vdots \\ r^{n-1} \end{bmatrix}$$

$\Rightarrow y_1$  is an e-value of the circulant matrix.

Next, consider  $\Phi(j, k) = \left( w_{j-1}^{k-1} \right) = e^{-\frac{2\pi i}{n}(j-1)(k-1)}$ ,  $\Phi^{-1} = \frac{1}{N} \Phi^*$  and

$$\lambda(j) = \sum_{l=1}^n v(l) e^{-\frac{2\pi i}{n}(j-1)(l-1)}.$$

By direct computing, it can be shown  $C$  is diagonalizable and

$$C = \Phi^{-1} \Lambda \Phi \quad \text{where } \Lambda = \begin{bmatrix} \lambda(1) & & 0 \\ & \ddots & \\ 0 & & \lambda(n) \end{bmatrix}.$$

Moreover,  $\Lambda = \text{diag}(\lambda_i) = \text{diag}(\Phi \cdot v)$ , here  $v = [v_0, v_1, \dots, v_{n-1}]$ .

The above equalities implies that the convolution  $y = Cx$  can be carried out by 3 *FFT* and one vector pointwise multiplication. The convolution algorithm is as following:

$$\left\{ \begin{array}{l} 1. \tilde{x} = \Phi x \\ 2. \tilde{v} = \Phi v \\ 3. z = \tilde{v} * \tilde{x} \text{ (pointwise multiplication)} \\ 4. y = \Phi z \end{array} \right.$$

Similarly, the deconvolution can be done in the same cost!

(The cost is down to  $n \log n$  from the cost  $O(n^2)$  of the direct matrix vector product)

Now, let's come back to solve the system (++) for the case  $m \gg n$

$$\Phi_{n \times m}^T [\Phi_{m \times n} x - y] = 0 \quad \text{--- (++)}$$

Suppose one can find some transformation  $Q^T$  such that

$$Q^T \Phi_{m \times n} = \begin{bmatrix} \tilde{R}_{n \times n} \\ 0 \end{bmatrix} = R \quad \text{here } \tilde{R} \text{ is nonsingular.} \quad \left( \begin{array}{l} Q^T \text{ exists since} \\ \text{we can always use } G.E. \\ \text{to do it.} \end{array} \right)$$

$$\begin{aligned} \text{Then (++)} &\Rightarrow R^T Q^T [QRx - y] = 0 \\ &\Rightarrow R^T [(Q^T Q)Rx - Q^T y] = 0 \end{aligned}$$

Suppose one can find  $Q$  that is orthogonal. ( $Q^T Q = I$ )



Then the system becomes

$$R^T [Rx - Q^T y] = 0 \quad \left( \left[ \begin{array}{c|c} \tilde{R}^* & 0 \end{array} \right] \left( \left[ \begin{array}{c} \tilde{R} \\ 0 \end{array} \right] x - Q^T y \right) = 0 \right)$$

One only needs to solve  $\tilde{R}_{n \times n} \tilde{x} = \tilde{y}$ .

This is easy to solve since  $n \ll m$ .

So the question now becomes that given a matrix  $A_{m \times n}$ , how to find an orthogonal transformation  $Q$  such that

$$A = QR$$

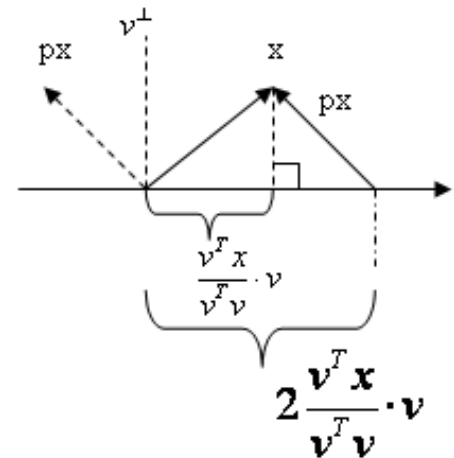
We now introduce the  $QR$  decomposition of  $A$  in the following:

Consider the House-Holder transformation matrix

$$p = I - \frac{2}{v^T v} v v^T$$

$$\Rightarrow px = x - \frac{2}{v^T v} v (v^T x) = x - \frac{2(v^T x)}{v^T v} \cdot v$$

It is clear that  $px$  is the reflection of  $x$  with respect to  $v^\perp$

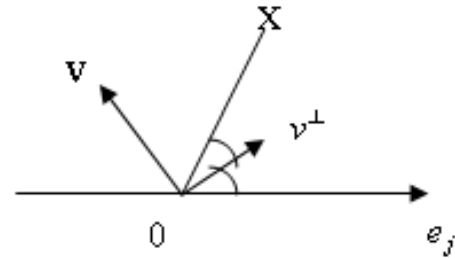


Basic idea:

Given a vector  $x$ , try to find  $v$  such that

(&)  $px = \beta \vec{e}_1$  (or  $\vec{e}_j$  for any given  $j$ ),

here  $\beta$  is a constant.



$$\left. \begin{array}{l} v = x + \alpha e_1 \\ \text{consider } v^T x = x^T x + \alpha x_1 \\ v^T v = x^T x + 2\alpha x_1 + \alpha^2 \end{array} \right\} \Rightarrow px = x - \frac{2vv^T}{v^T v} x = x - \frac{2(x + \alpha e_1) \cdot (x^T x + \alpha x_1)}{x^T x + 2\alpha x_1 + \alpha^2}$$

$$= \left( 1 - \frac{2(x^T x + \alpha x_1)}{\|x\|^2 + 2\alpha x_1 + \alpha^2} \right) x - \underbrace{\frac{2\alpha(x^T x + \alpha x_1)}{\|x\|^2 + 2\alpha x_1 + \alpha^2}}_{\beta} e_1$$

To achieve (&), we simply choose  $\alpha$  such that  $1 - \frac{2(x^T x + \alpha x_1)}{\|x\|^2 + 2\alpha x_1 + \alpha^2} = 0 \Rightarrow \alpha = \|x\|$   
 $\beta = \alpha = \|x\|$

Notice that

- (1)  $p^T p = I \Rightarrow p$  is an orthogonal transformation.  
 (2) Given a matrix  $A = [A_1, A_2, \dots, A_n]$ , one can construct

$p_1$  such that  $p_1 A_1 = \beta_1 e_1$

$$p_1 A = \begin{bmatrix} \beta_1 & * & * & \dots & * \\ 0 & & * & \dots & * \\ 0 & \tilde{A}_2 & * & & * \\ \vdots & & \vdots & & \vdots \\ 0 & & * & \dots & * \end{bmatrix}$$

||  
x

Similarly, by constructions  $p_2$  such that  $p_2 \tilde{A}_2 = \begin{bmatrix} \beta_2 \\ 0 \\ \vdots \\ 0 \end{bmatrix}$ , we have  $\left[ \begin{array}{c|c} 1 & 0 \\ \hline 0 & p_2 \end{array} \right] p_1 A = \begin{bmatrix} \beta_1 & * & * & * & \dots & * \\ 0 & \beta_2 & * & * & \dots & * \\ 0 & 0 & & * & \dots & * \\ \vdots & \vdots & \tilde{A}_3 & \vdots & & \vdots \\ \vdots & \vdots & & \vdots & & \vdots \\ 0 & 0 & & * & \dots & * \end{bmatrix}$

Repeating the above process, one has

$$Q^T = \underbrace{\begin{bmatrix} I & 0 \\ 0 & p_n \end{bmatrix}}_{P_n} \cdot \underbrace{\begin{bmatrix} I & 0 \\ 0 & p_{n-1} \end{bmatrix}}_{P_{n-1}} \cdots \underbrace{\begin{bmatrix} I & 0 \\ 0 & p_2 \end{bmatrix}}_{P_2} \cdot \underbrace{p_1}_{P_1} \text{ is orthogonal.}$$

and  $Q^T A = R$  where  $R =$

$$\begin{bmatrix} \beta_1 & & & & * \\ & \beta_2 & & & \\ & & \ddots & & \\ & & & \ddots & \\ & & & & \ddots \\ \hline & & & & & 0 \end{bmatrix}$$

In practice, we never construct  $P_i$ ,  $i = 1 \sim n$ , explicitly.

Since  $pA = \left( I - \frac{2vv^T}{v^T v} \right) A \underset{r = \frac{2}{v^T v}}{=} \left( I - rvv^T \right) A = \underbrace{A - rvw^T}_{\text{cost } O(m \times n)}, \quad \underbrace{w = vA^T v}_{m \times n \text{ operation}}$

Total cost for  $QR$  is about  $\sum_{i=0}^{n-1} (m-i)(n-i) \approx O(mn^2)$