

Some derivation for finding orthogonal "points" maintaining K values:

Say some point  $P = \begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ \vdots \\ P_n \end{bmatrix}$ ,  $P \in \mathbb{R}$

$$V_{\text{eff}} = K_1 \begin{bmatrix} s_{11} \\ s_{12} \\ s_{13} \\ \vdots \\ s_{1n} \end{bmatrix} + K_2 \begin{bmatrix} s_{21} \\ s_{22} \\ s_{23} \\ \vdots \\ s_{2n} \end{bmatrix} + \dots + K_r \begin{bmatrix} s_{r1} \\ s_{r2} \\ s_{r3} \\ \vdots \\ s_{rn} \end{bmatrix}, \quad V \in \mathbb{R}.$$

(for  $V$ 's not starting at 0,0, transpose first by  $P$ ).

minimise objective function:

$$f(K) = (p - V(K))^2 = (p_1 - (k_1 s_{11} + k_2 s_{21} + \dots + k_r s_{r1}))^2 + (p_2 - (k_1 s_{12} + k_2 s_{22} + \dots + k_r s_{r2}))^2 + \dots + (p_n - (k_1 s_{1n} + k_2 s_{2n} + \dots + k_r s_{rn}))^2$$

take partial derivative:

$$\frac{df}{dk} = \left[ \frac{df}{dk_1} \frac{df}{dk_2} \dots \frac{df}{dk_r} \right]$$

$$0 = \frac{\partial \mathcal{L}}{\partial k_1} = 2(-s_{11}) \left( p_1 - (k_1 s_{11} + k_2 s_{21} \dots) \right) + 2(-s_{12}) \left( p_2 - (k_1 s_{12} + k_2 s_{22} \dots) \right)$$

$r$  unknowns,  $r$  equations

formulates a set of  $r$  simultaneous equations

In form  $Ax = b$ , where

$$A = \begin{bmatrix} \sum_{i=1}^r S_{1i}^2 & \sum_{i=1}^r S_{1i} S_{2i} & \sum_{i=1}^r S_{1i} S_{3i} & \dots & \sum_{i=1}^r S_{1i} S_{ri} \\ \sum_{i=1}^r S_{2i}^2 & \sum_{i=1}^r S_{2i} S_{3i} & \dots & \dots & \sum_{i=1}^r S_{2i} S_{ri} \\ \vdots & \vdots & \ddots & \ddots & \vdots \\ \sum_{i=1}^r S_{ri}^2 \end{bmatrix} \quad (\text{Note: symmetric})$$

$$b = \begin{bmatrix} \sum_{i=1}^r p_i s_{1i} \\ \sum_{i=1}^r p_i s_{2i} \\ \vdots \\ \sum_{i=1}^r p_i s_{ri} \end{bmatrix} \quad X = \begin{bmatrix} k_1 \\ k_2 \\ \vdots \\ k_r \end{bmatrix}$$

Using python's `np.linalg.solve` function (could exist a faster way for symmetric matrices?)  
solved for  $k$

Seems to work well in the context of the algorithm discussed last week.

(solved for 2  $1,000 \times 1,000$  vectors in 100,000 Dimensional space reasonably quickly.)  $\rightarrow$  only performs 5-4 iterations. Can't tell if this is good.

Time complexity:  $O(r^3) \rightarrow$  in theory, doesn't really scale with  $n$ ?

Iteration count seems to go DOWN with scaling  $n$  and  $r$ , which is strange but could be a property of the system. Made sure to normalise RMS checking metric.

Significantly faster than algorithm from last time, often requiring 1000+ x less iterations to converge.

```

No size array provided, setting to default.
(array([ 1. , -166.3, 312.6, 143.1, -15.5, -163.4, -17.9, -237.1,
        12.3, 95.8]), array([ 17. , -279.1, -274.4, -166.3, 23.8, -224.1, 109.9, -29.4,
        -84.6, -21.8]), 12583)
Made it here!
(array([ 1.0155751, -166.29187912, 312.64925603, 143.12072228,
        -15.54382458, -163.378709 , -17.90770774, -237.06126441,
        12.26956715, 95.77559008]), array([ 16.98606249, -279.07444188, -274.35807456, -166.27144871,
        23.75668287, -224.06748873, 109.93861973, -29.41294294,
        -84.61245244, -21.78368758]), 7)
  
```

*Method 1* (points to first array)  
*MUCH higher* (points to 12583)  
*Good accuracy* (points to second array)  
*new method* (points to third array)  
*Much lower* (points to 7)

Potential problems / questions:

1. Bottlenecked test bench:

Fortunately, the current bottleneck in computation is the generation method. Can be optimised, probably, but generating the aforementioned 1000 D vectors in 100,000 D space requires the random generation of 100,000,000 random numbers, each.

Could need some parallelism.

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## 2. Accuracy.

Method 1 is too slow to reasonably run on higher spaces. Hard to verify how accurate the algorithm is at higher dimensional spaces, especially since the iteration count is so small.

## 3. Is solving the set of simultaneous equations really the best way? Can't tell.

## 4. Would a similar objective function exist directly between two vectors?

i.e. minimise:

$$f(k_1, k_2) = (k_1 v_1 - k_2 v_2)^2$$

+ more but cannot remember off the top of my head.