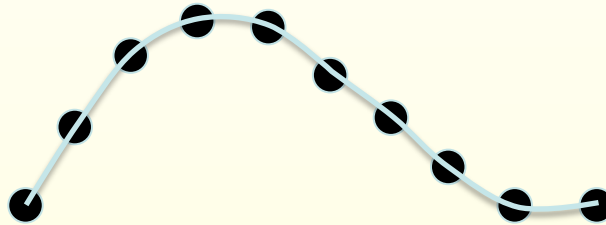


# Normal Estimation for a Curve

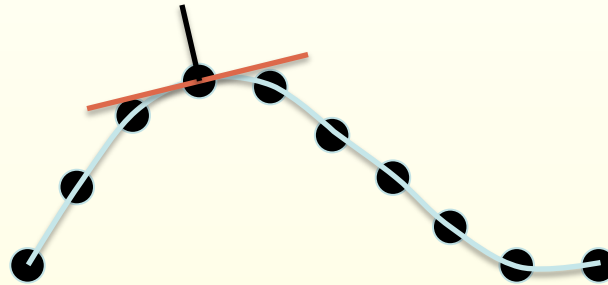
Assume we have a clean sampling of the curve.



Our goal is to find the best approximation of the tangent direction, and thus of the normal to the curve.

# Normal Estimation for a Curve

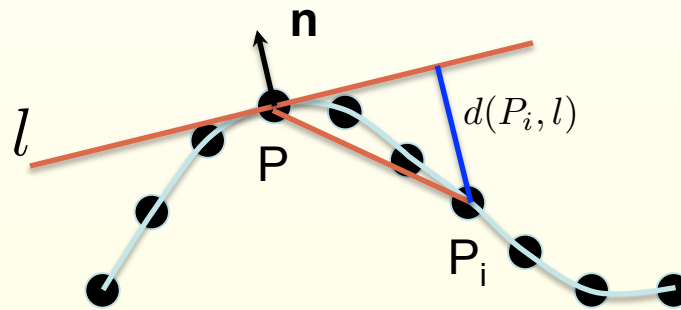
Assume we have a clean sampling of the curve.



Our goal is to find the best approximation of the tangent direction, and thus of the normal to the curve.

# Normal Estimation for a Curve

Assume we have a clean sampling of the curve.



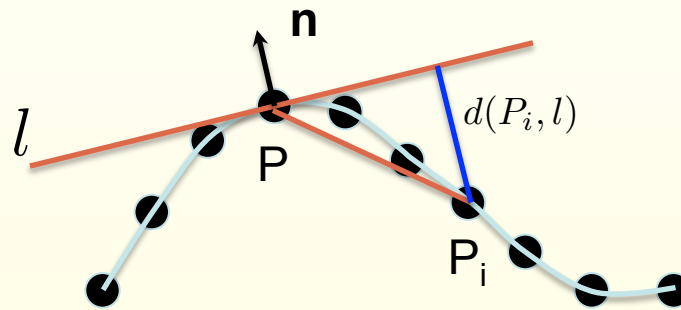
Goal: find best approximation of the normal at P.

Method: Given line  $l$  through P with normal  $\mathbf{n}$ , the distance to the tangent line from another close-by point  $p_i$ :

$$d(p_i, l)^2 = \frac{((p_i - P)^T \mathbf{n})^2}{\mathbf{n}^T \mathbf{n}} = ((p_i - P)^T \mathbf{n})^2 \text{ if } \|\mathbf{n}\| = 1$$

# Normal Estimation for a Curve

Assume we have a clean sampling of the curve.

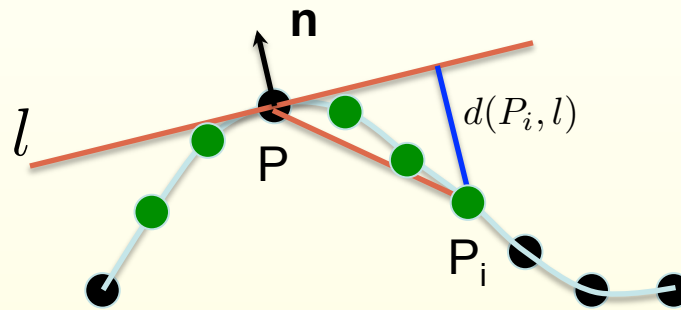


Goal: find best approximation of the normal at P.

Method: Find the line that best fits the neighborhood of P. This will approximate the tangent line.

# Normal Estimation for a Curve

Assume we have a clean sampling of the curve.



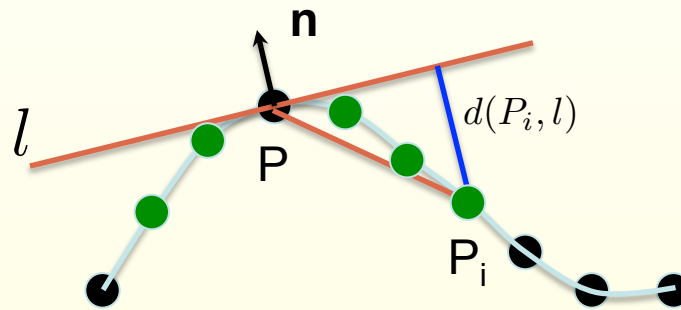
Goal: find best approximation of the normal at  $P$ .

Equivalently: Find unit-length vector  $\mathbf{n}$ , minimizing  $\sum_{i=1}^k d(p_i, l)^2$  for a set of  $k$  points (e.g.  $k$  nearest neighbors of  $P$ ).

$$\mathbf{n}_{\text{opt}} = \arg \min_{\|\mathbf{n}\|=1} \sum_{i=1}^k ((p_i - P)^T \mathbf{n})^2$$

# Normal Estimation for a Curve

Assume we have a clean sampling of the curve.



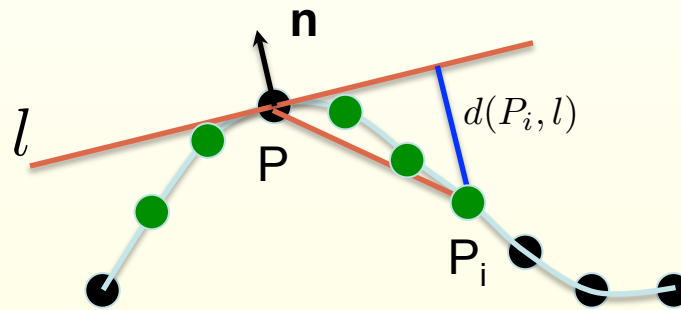
Using Lagrange multiplier:

$$\frac{\partial}{\partial \mathbf{n}} \left( \sum_{i=1}^k ((p_i - P)^T \mathbf{n})^2 \right) - \lambda \frac{\partial}{\partial \mathbf{n}} (\mathbf{n}^T \mathbf{n}) = 0$$

$$\sum_{i=1}^k 2(p_i - P)(p_i - P)^T \mathbf{n} = 2\lambda \mathbf{n}$$

# Normal Estimation for a Curve

Assume we have a clean sampling of the curve.



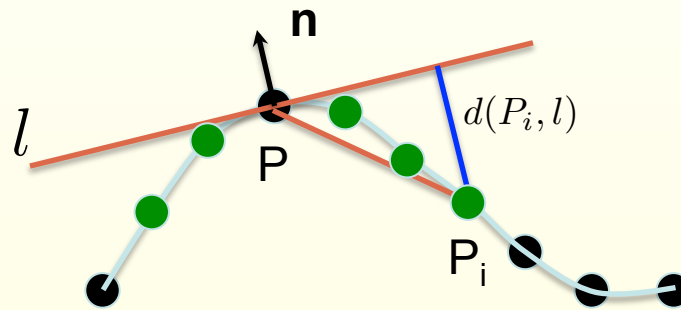
Using Lagrange multiplier:

$$\frac{\partial}{\partial \mathbf{n}} \left( \sum_{i=1}^k ((p_i - P)^T \mathbf{n})^2 \right) - \lambda \frac{\partial}{\partial \mathbf{n}} (\mathbf{n}^T \mathbf{n}) = 0$$

$$\left( \sum_{i=1}^k (p_i - P)(p_i - P)^T \right) \mathbf{n} = \lambda \mathbf{n} \implies C \mathbf{n} = \lambda \mathbf{n}$$

# Normal Estimation for a Curve

Assume we have a clean sampling of the curve.



The normal  $\mathbf{n}$  must be an eigenvector of the matrix:

$$C\mathbf{n} = \lambda\mathbf{n} \quad C = \sum_{i=1}^k (p_i - P)(p_i - P)^T$$

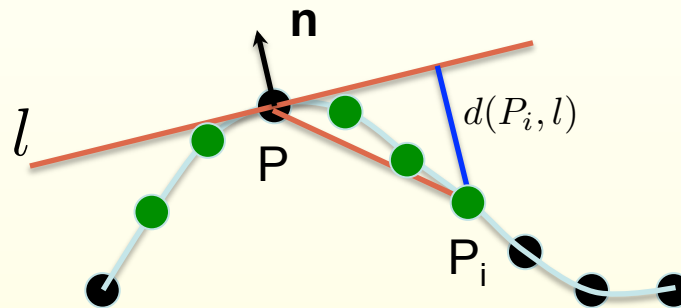
Moreover, since:

$$\mathbf{n}_{\text{opt}} = \arg \min_{\|\mathbf{n}\|=1} \sum_{i=1}^k ((p_i - P)^T \mathbf{n})^2 = \arg \min_{\|\mathbf{n}\|=1} \mathbf{n}^T C \mathbf{n}$$



# Normal Estimation for a Curve

Assume we have a clean sampling of the curve.



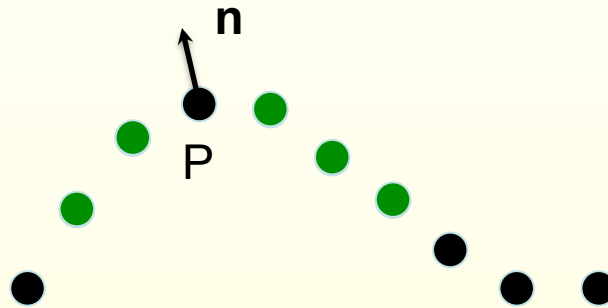
The normal  $\mathbf{n}$  must be an eigenvector of the matrix:

$$C\mathbf{n} = \lambda\mathbf{n} \quad C = \sum_{i=1}^k (p_i - P)(p_i - P)^T$$

Moreover,  $\mathbf{n}_{\text{opt}}$  must be the eigenvector corresponding to the **smallest eigenvalue** of  $C$ .

# Normal Estimation for a Curve

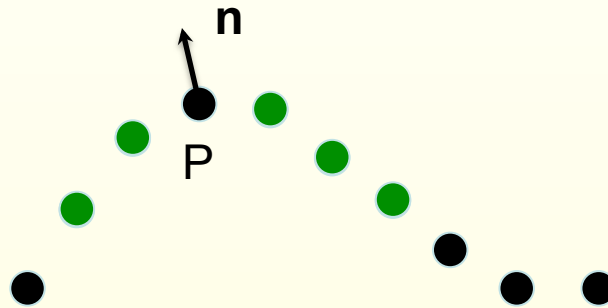
Method Outline (PCA):



1. Given a point  $P$  in the point cloud, find its  $k$  nearest neighbors.
2. Compute  $C = \sum_{i=1}^k (p_i - P)(p_i - P)^T$
3. **n**: eigenvector corresponding to the smallest eigenvalue of  $C$ .

# Normal Estimation for a Curve

Method Outline (PCA):



1. Given a point  $P$  in the point cloud, find its  $k$  nearest neighbors.
2. Compute  $C = \sum_{i=1}^k (p_i - P)(p_i - P)^T$
3.  $\mathbf{n}$ : eigenvector corresponding to the smallest eigenvalue of  $C$ .

**Same principle for surfaces!**