

1 Intuition

1.1 Training and Prediction

- In training stage, KNN simply memorizes the training data (effectively a NOP operation)
- In prediction stage, for each **test** image KNN finds the *nearest* training data (that it previously memorized)
- As number of training samples approaches infinity, KNN can represent any function (subject to many technical conditions)
 - However, this suffers from *curse of dimensionality*
 - For uniform coverage of training space, number of training points increases exponentially with dimension

1.2 Distance Metrics

L1 distance:

$$d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$$

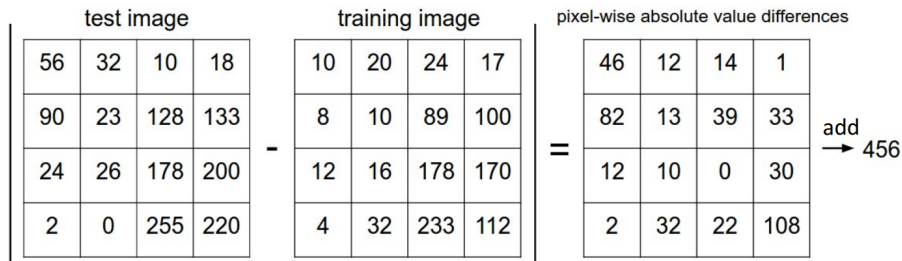
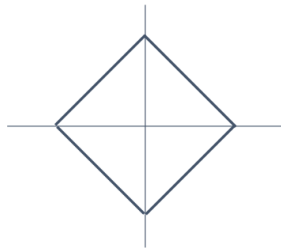


Figure 1

L1 (Manhattan) distance

$$d_1(I_1, I_2) = \sum_p |I_1^p - I_2^p|$$



L2 (Euclidean) distance

$$d_2(I_1, I_2) = \sqrt{\sum_p (I_1^p - I_2^p)^2}$$

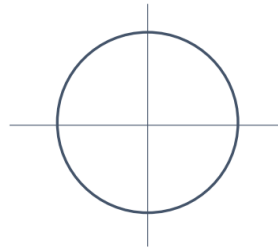
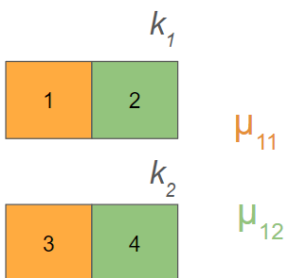


Figure 2

2 Per-pixel calculations



- General mean $\mu = \frac{1+2+3+4}{1*2*2}$

- Pixel-wise mean $\mu_{ij} = \begin{bmatrix} \mu_{11} \\ \mu_{12} \end{bmatrix} = \begin{bmatrix} \frac{1+3}{2} \\ \frac{2+4}{2} \end{bmatrix} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}$

Figure 3: $p^{(k_1)}$ and $p^{(k_2)}$

3 L2 Distance - Fully vectorised

$$\begin{aligned}
d_2(A, B) &= \sqrt{\sum_p (A_p - B_p)^2} ; \text{ Where } \mathbf{A} \text{ and } \mathbf{B} \text{ are vectors indexed via } p \\
&= \sqrt{\sum_p \{ (A_p)^2 - 2(A_p \cdot B_p) + (B_p)^2 \}} \\
&= \sqrt{\left\{ \sum_p (A_p)^2 \right\} - 2 \left\{ \sum_p (A_p \cdot B_p) \right\} + \left\{ \sum_p (B_p)^2 \right\}} \\
&= \sqrt{\left\{ \sum_p (A_p)^2 \right\} - 2 \left\{ \mathbf{A} \mathbf{B}^T \right\} + \left\{ \sum_p (B_p)^2 \right\}} \\
&= \sqrt{\left\{ \sum_p (A_p)^2 \right\} + \left\{ \sum_p (B_p)^2 \right\} - 2 \left\{ \mathbf{A} \mathbf{B}^T \right\}}
\end{aligned}$$

3.1 Context

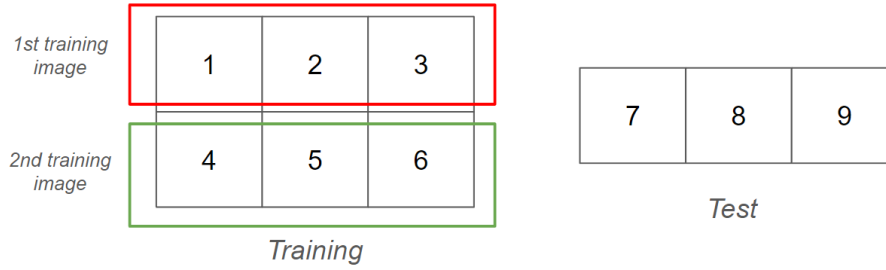


Figure 4

- Training = $\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix}$, Test = $\begin{bmatrix} 7 & 8 & 9 \end{bmatrix}$
- We want to calculate the L2 distance between test image and every training image

3.1.1 One loop

1. Broadcast; $(Tr - Te)_{broadcast} = \begin{bmatrix} 1-7 & 2-8 & 3-9 \\ 4-7 & 5-8 & 6-9 \end{bmatrix} = \begin{bmatrix} -6 & -6 & -6 \\ -3 & -3 & -3 \end{bmatrix}$
2. Square terms; $(Tr - Te)_{broadcast}^2 = \begin{bmatrix} 36 & 36 & 36 \\ 9 & 9 & 9 \end{bmatrix}$
3. Sum along rows; $\sum_{rows} (Tr - Te)_{broadcast}^2 = \begin{bmatrix} 36 + 36 + 36 \\ 9 + 9 + 9 \end{bmatrix} = \begin{bmatrix} 108 \\ 27 \end{bmatrix}$
4. Square root; $\sqrt{\sum_{rows} (Tr - Te)_{broadcast}^2} = \begin{bmatrix} \sqrt{108} \\ \sqrt{27} \end{bmatrix}$

3.1.2 No loop

1. Square **elements of** training matrix; $Tr_{squared} = \begin{bmatrix} 1 & 4 & 9 \\ 16 & 25 & 36 \end{bmatrix}$
 - 1.1. $\sum_{row} Tr_{squared} = \begin{bmatrix} 1 + 4 + 9 \\ 16 + 25 + 36 \end{bmatrix} = \begin{bmatrix} 14 \\ 77 \end{bmatrix}$
2. Square **elements of** test matrix; $Te_{squared} = \begin{bmatrix} 49 & 64 & 81 \end{bmatrix}$
 - 2.1. $\sum_{row} Te_{squared} = \begin{bmatrix} 49 + 64 + 81 \end{bmatrix} = \begin{bmatrix} 194 \end{bmatrix}$
3. Broadcast; $\left(\sum_{row} Tr_{squared} + \sum_{row} Te_{squared} \right)_{broadcast} = \begin{bmatrix} 14 + 194 \\ 77 + 194 \end{bmatrix} = \begin{bmatrix} 208 \\ 271 \end{bmatrix}$
4. $2(TrTe^T) = 2 \cdot \begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \end{bmatrix} \begin{bmatrix} 7 \\ 8 \\ 9 \end{bmatrix} = \begin{bmatrix} 100 \\ 244 \end{bmatrix}$

$$5. \left(\sum_{row} Tr_{squared} + \sum_{row} Te_{squared} \right)_{broadcast} - 2(\mathbf{TrTe}^T)$$