7. Correlation & Clustering

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Pearson Correlation Coefficient

- Pearson correlation coefficient (PCC)
 - Pearson product-moment correlation coefficient

$$\rho_{x,y} = \frac{\text{cov}(X,Y)}{\sigma_{x}\sigma_{y}} = \frac{\text{E}[(X - \mu_{x})(Y - \mu_{y})]}{\sqrt{\text{E}[(X - \mu_{x})^{2}]E[(Y - \mu_{y})^{2}]}}$$

$$= \frac{\text{E}[XY] - \text{E}[X]E[Y]}{\sqrt{(\text{E}[X^{2}] - (\text{E}[X])^{2})(\text{E}[Y^{2}] - (\text{E}[Y])^{2})}}$$

$$= \frac{\sum (x_{i} - \mu_{x})(y_{i} - \mu_{y})}{\sqrt{\sum (x_{i} - \mu_{x})^{2}\sum (y_{i} - \mu_{y})^{2}}}$$

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Pseudo Random Number

KhuGleBase.cpp (1)

```
double GetPearsonCoefficient(std::vector<std::pair<double, double>>> Data) {
   double Mean1 = 0, Mean2 = 0, Mean12 = 0;
   double SquaredMean1 = 0, SquaredMean2 = 0;

   for(auto EachData : Data) {
      Mean1 += EachData.first;
      Mean2 += EachData.second;
      Mean12 += EachData.first*EachData.second;

   SquaredMean1 += EachData.first*EachData.first;
   SquaredMean2 += EachData.second*EachData.second;
}
```

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Pearson Correlation Coefficient

KhuGleBase.cpp (2)

```
Mean1 /= Data.size();
Mean2 /= Data.size();
Mean12 /= Data.size();

SquaredMean1 /= Data.size();

SquaredMean2 /= Data.size();

double sigma1 = sqrt(SquaredMean1-Mean1*Mean1);
double sigma2 = sqrt(SquaredMean2-Mean2*Mean2);

if(sigma1 == 0 || sigma2 == 0) return 0;

return (Mean12 - Mean1*Mean2)/(sigma1*sigma2);
}
```

Main.cpp (1)

```
class CCorrelationLayer : public CKhuGleLayer {
public:
 std::vector<CKhuGleSprite *> m_Point;
 CCorrelationLayer(int nW, int nH, KgColor24 bgColor,
   CKgPoint ptPos = CKgPoint(0, 0)): CKhuGleLayer(nW, nH, bgColor, ptPos) {
   GenerateData(200);
 void GenerateData(int nCnt);
};
void CCorrelationLayer::GenerateData(int nCnt) {
 unsigned int seed = (unsigned int)std::chrono::
                       system_clock::now().time_since_epoch().count();
  std::default_random_engine generator(seed);
 std::uniform_real_distribution<double> uniform_dist(0, 1);
 for(auto &Child : m_Children)
   delete Child;
 m_Children.clear();
 m_Point.clear();
```

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Main.cpp (2)

```
double mean1 = uniform_dist(generator);
double mean2 = uniform_dist(generator);

double sigma1 = uniform_dist(generator)/2.;
double sigma2 = uniform_dist(generator)/2.;

double rotate = uniform_dist(generator)*Pi;

std::normal_distribution<double> normal_dist1(mean1, sigma1);
std::normal_distribution<double> normal_dist2(mean2, sigma2);
```

```
double x, y;
for(int i = 0 ; i < nCnt ; i++) {
   double xx = normal_dist1(generator);
   double yy = normal_dist2(generator);

x = (xx-mean1)*cos(rotate) - (yy-mean2)*sin(rotate) + mean1;
y = (xx-mean1)*sin(rotate) + (yy-mean2)*cos(rotate) + mean2;

x = (x*m_nW - m_nW/2)*0.6 + m_nW/2;
y = (y*m_nH - m_nH/2)*0.6 + m_nH/2;

CKhuGleSprite *Point = new CKhuGleSprite(GP_STYPE_ELLIPSE, GP_CTYPE_DYNAMIC,
   CKgLine(CKgPoint((int)x-2, (int)y-2), CKgPoint((int)x+2, (int)y+2)),
   KG_COLOR_24_RGB(255, 255, 255), true, 30);

m_Point.push_back(Point);
AddChild(Point);
}
</pre>
```

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Main.cpp (4)

```
class CClusterLayer : public CKhuGleLayer {
    ...
};

class CCorrelationClustering : public CKhuGleWin {
    public:
        CKhuGleScene *m_pCorrelationScene;
        CKhuGleScene *m_pClusteringScene;

        CCorrelationLayer *m_pCorrelationLayer;
        CClusterLayer *m_pClusteringLayer;

        bool m_bCorrelationScene;

        CCorrelationClustering(int nW, int nH);
        virtual ~CCorrelationClustering() {
            m_pScene = nullptr;
            delete m_pCorrelationScene;
            delete m_pClusteringScene;
        }
        void Update();
};
```

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Main.cpp (6)

```
void CCorrelationClustering::Update() {
 if(m_bKeyPressed['M']) {
   m_bCorrelationScene = !m_bCorrelationScene;
   if(m_bCorrelationScene)
     m_pScene = m_pCorrelationScene;
     m pScene = m pClusteringScene;
   m_bKeyPressed['M'] = false;
  if(m_bKeyPressed['S']) {
   if(m_bCorrelationScene) {
     std::vector<std::pair<double, double>> Data;
     for(auto Point : m_pCorrelationLayer->m_Point)
       Data.push_back({Point->m_Center.x, Point->m_Center.y});
     double pcc = GetPearsonCoefficient(Data);
      std::cout << pcc << std::endl;</pre>
   else {
   m_bKeyPressed['S'] = false;
```

```
if(m_bKeyPressed['N']) {
   if(m_bCorrelationScene)
     m_pCorrelationLayer->GenerateData(200);
   else {
   m bKeyPressed['N'] = false;
 }
 m_pScene->Render();
 if(m_bCorrelationScene)
   DrawSceneTextPos("Correlation && Clustering (Correlation scene)", CKgPoint(0, 0));
   DrawSceneTextPos("Correlation && Clustering (Clustering scene)", CKgPoint(0, 0));
 CKhuGleWin::Update();
int main() {
 CCorrelationClustering *pCorrelationClustering
   = new CCorrelationClustering(640, 480);
 KhuGleWinInit(pCorrelationClustering);
 return 0;
```

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k-Means Clustering (1)

- k-Means Clustering
 - · Centroid-based method
 - · Iterative refinement method
 - c₀={c₁, c₂, ...c_k} ← random
 while iteration or c is not change (c_i = c_{i-1}) do
 assign each sample to the cluster which has the closest c
 compute new centroids (c_i) for each cluster (sample mean)

end while



k-Means Clustering (2)

- Static k value
- Dependent results on initial centroids
- Spherical and equally sized clustering

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Main.cpp (1)

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```
class CKhuGleSprite2 : public CKhuGleSprite {
public:
    int m_nClusterIndex;
    CKhuGleSprite2(int nType, int nCollisionType, CKgLine lnLine,
        KgColor24 fgColor, bool bFill, int nSliceOrWidth = 100,
        int nClusterIndex = 0)
    : CKhuGleSprite(nType, nCollisionType, lnLine, fgColor, bFill, nSliceOrWidth)
    {
        m_nClusterIndex = nClusterIndex;
    }
};
```

```
class CClusterLayer : public CKhuGleLayer {
public:
    std::vector<CKhuGleSprite2 *> m_Center;
    std::vector<CKhuGleSprite2 *> m_Point;
    int m_nClusterNum, m_nStep;

CClusterLayer(int nW, int nH, KgColor24 bgColor,
    CKgPoint ptPos = CKgPoint(0, 0)) : CKhuGleLayer(nW, nH, bgColor, ptPos) {
    m_nClusterNum = 3;

    GenerateData(m_nClusterNum, 50);
    m_nStep = 0;
}

void GenerateData(int nCluster, int nCnt);
};
```

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Main.cpp (3)

```
void CClusterLayer::GenerateData(int nCluster, int nCnt) {
 unsigned int seed = (unsigned int)std::chrono
   ::system_clock::now().time_since_epoch().count();
 std::default_random_engine generator(seed);
 std::uniform_real_distribution<double> uniform_dist(0, 1);
 for(auto &Child : m_Children)
   delete Child;
 m_Children.clear();
 m_Center.clear();
 m_Point.clear();
 for(int i = 0 ; i < m_nClusterNum ; ++i) {</pre>
   CKhuGleSprite2 *Center = new CKhuGleSprite2(GP_STYPE_ELLIPSE,
      GP_CTYPE_DYNAMIC, CKgLine(CKgPoint(m_nW/2-10, m_nH/2-10),
      CKgPoint(m_nW/2+10, m_nH/2+10)),
     KG_COLOR_24_RGB(i%2*255, i/2%2*255, i/4%2*255), false, 100);
   m_Center.push_back(Center);
   AddChild(Center);
```

```
for(int k = 0 ; k < nCluster ; ++k) {
   double mean1 = uniform_dist(generator);
   double mean2 = uniform_dist(generator)/10.;
   double sigma1 = uniform_dist(generator)/10.;
   double sigma2 = uniform_dist(generator)/10.;

   double rotate = uniform_dist(generator)*Pi;

std::normal_distribution<double> normal_dist1(mean1, sigma1);
   std::normal_distribution<double> normal_dist2(mean2, sigma2);
```

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Main.cpp (5)

```
double x, y;
    for(int i = 0 ; i < nCnt ; i++) {
     double xx = normal_dist1(generator);
     double yy = normal_dist2(generator);
     x = (xx-mean1)*cos(rotate) - (yy-mean2)*sin(rotate) + mean1;
     y = (xx-mean1)*sin(rotate) + (yy-mean2)*cos(rotate) + mean2;
     x = (x*m_nW - m_nW/2)*0.6 + m_nW/2;
     y = (y*m_nH - m_nH/2)*0.6 + m_nH/2;
     CKhuGleSprite2 *Point = new CKhuGleSprite2(GP_STYPE_ELLIPSE,
       GP_CTYPE_DYNAMIC,
        CKgLine(CKgPoint((int)x-2, (int)y-2), CKgPoint((int)x+2, (int)y+2)),
       KG_COLOR_24_RGB(255, 255, 255), true, 30);
     m Point.push back(Point);
     AddChild(Point);
   }
 }
}
```

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Main.cpp (7)

```
for(auto &Point : m_pClusteringLayer->m_Point) {
   int Index = Point->m_nClusterIndex;

   NewCenter[Index].first += Point->m_Center.x;
   NewCenter[Index].second += Point->m_Center.y;

   ClusterCnt[Index]++;
}
for(int k = 0 ; k < m_pClusteringLayer->m_nClusterNum ; ++k) {
   if(ClusterCnt[k] > 0)
        m_pClusteringLayer->m_Center[k]->MoveTo
        (NewCenter[k].first/ClusterCnt[k]);
    }
}
```

```
for(auto &Point : m_pClusteringLayer->m_Point) {
  double MinDist, Dist;
  for(int k = 0 ; k < m_pClusteringLayer->m_nClusterNum ; ++k) {
    Dist = sqrt((Point->m_Center.x
        - m_pClusteringLayer->m_Center[k]->m_Center.x)
       *(Point->m_Center.x - m_pClusteringLayer->m_Center[k]->m_Center.x) +
       (Point->m_Center.y - m_pClusteringLayer->m_Center[k]->m_Center.y)
       *(Point->m_Center.y - m_pClusteringLayer->m_Center[k]->m_Center.y));
    if(k == 0) {
      Point->m_nClusterIndex = k;
      MinDist = Dist;
    else if(Dist < MinDist) {</pre>
      Point->m_nClusterIndex = k;
      MinDist = Dist;
  Point->m_fgColor = KG_COLOR_24_RGB(Point->m_nClusterIndex%2*255,
    Point->m nClusterIndex/2%2*255, Point->m nClusterIndex/4%2*255);
++(m_pClusteringLayer->m_nStep);
m_bKeyPressed['S'] = false;
```

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Main.cpp (9)

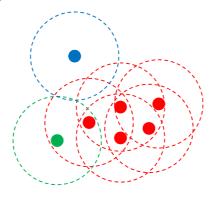
```
if(m_bKeyPressed['N']) {
   if(m_bCorrelationScene)
       m_pCorrelationLayer->GenerateData(200);
   else {
       m_pClusteringLayer->GenerateData(m_pClusteringLayer->m_nClusterNum, 50);
       m_pClusteringLayer->m_nStep = 0;
   }
   m_bKeyPressed['N'] = false;
}

m_pScene->Render();
...
}
int main() {
...
}
```

Practice VI (1)

DBSCAN

- Density-based spatial clustering of application with noise
- · Density-based clustering
- Core points: at least τ points with distance ϵ
- Border points: reachable from a core points
- Outliers: not core points and not reachable form any core points



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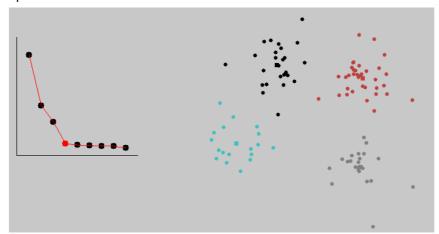
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Practice VI (2)

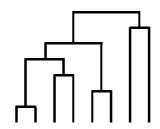
· Elbow method

- Determining the number of clusters
- # of clusters vs. sum of squared distance
- SSD (sum of squared distance, sse: sum of squared error)
 - Sum of squared distance from the cluster centroid



Advanced Courses (1)

- · Connectivity-based clustering
 - · Merge for split



- Clustering evaluation
 - Known class labels
 - Precision
 - RI (rand index)
 - Unknown class labels
 - Sum of squared distance
 - · Silhouette value

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Advanced Courses (2)

- Cross correlation
 - Similarity, matching score
 - Dot product

$$f(t) \otimes g(t) \triangleq \int_{-\infty}^{\infty} f^{*}(\tau)g(\tau+t)d\tau$$

$$f(t) * g(t) \triangleq \int_{-\infty}^{\infty} f(\tau)g(t-\tau)d\tau$$

$$\rho_{x,y} = \frac{\text{cov}(X,Y)}{\sigma_x \sigma_y} = \frac{\text{E}\left[\left(X - \mu_x\right)\left(Y - \mu_y\right)\right]}{\sigma_x \sigma_y} = \frac{1}{N} \frac{\left(X - \mu_x\right)\left(Y - \mu_y\right)}{\sigma_x \sigma_y}$$

Cosine similarity

$$\mathbf{a} \cdot \mathbf{b} = \|\mathbf{a}\| \|\mathbf{b}\| \cos \theta$$

$$\cos\theta = \frac{\mathbf{a} \cdot \mathbf{b}}{\|\mathbf{a}\| \|\mathbf{b}\|}$$

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