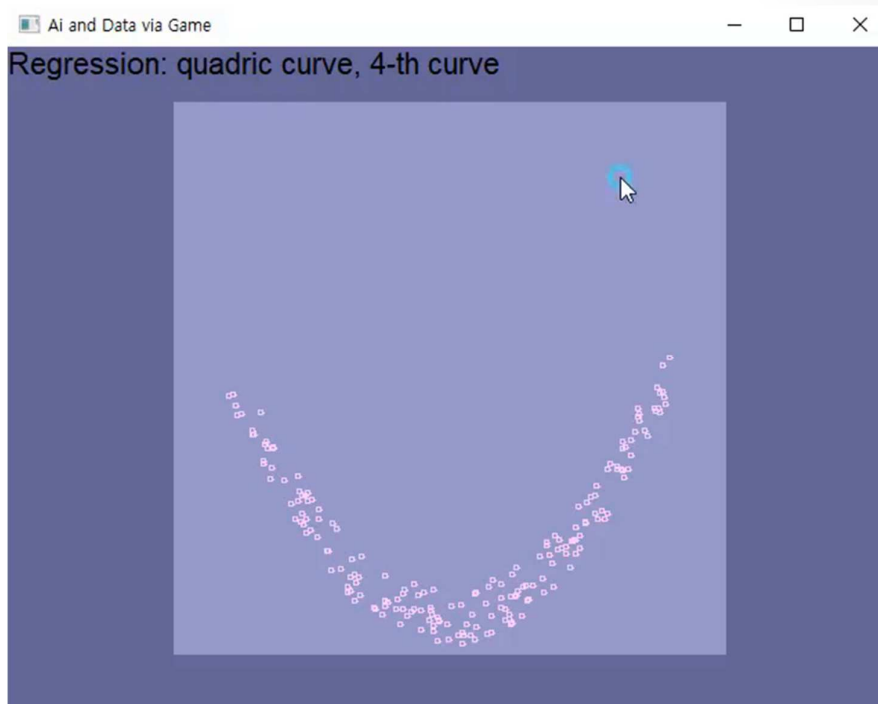


## 8. Regression



# Regression (1)

- Regression

- Modeling the relationship between a **dependent variable** and **one or more independent variables**

$$y = ax + b + \varepsilon$$

$$y = ax_1 + bx_2 + c + \varepsilon$$

- $\varepsilon$ : residual (error)

- Linear regression, multiple linear regression, polynomial regression
- Nonlinear regression

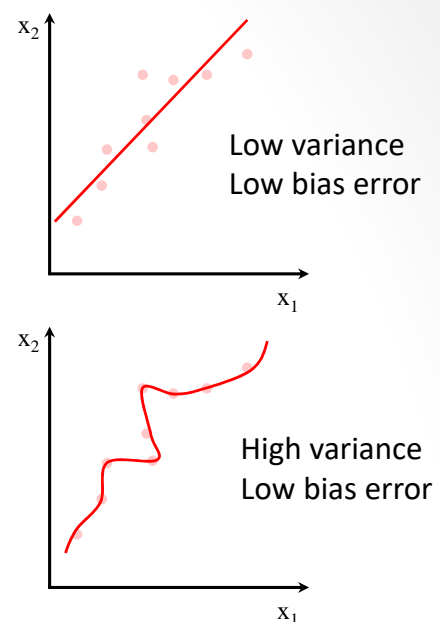
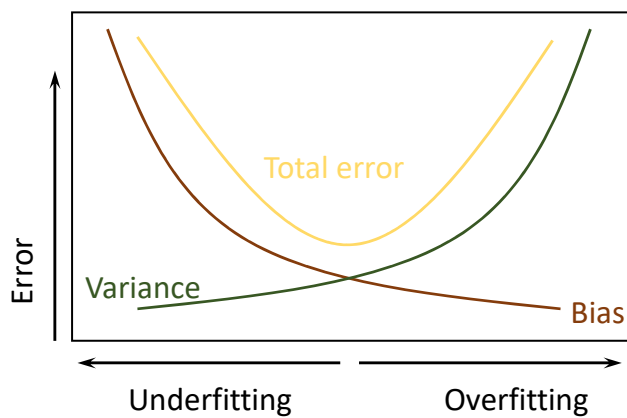
$$y = ax_1 + bx_2 + cx_3 + d$$

$$y = ax^3 + bx^2 + cx + d$$

# Regression (2)

- Bias-variance trade off

- Bias error and variance



## Regression (3)

- Least squares regression
 
$$\begin{aligned} y_1 &= ax_1 + b \\ y_2 &= ax_2 + b \\ y_3 &= ax_3 + b \\ &\vdots \end{aligned}$$

SSE (Sum of squared errors)

$$\mathbf{X}\mathbf{w} = \hat{\mathbf{y}}$$

$$\text{SSE} = Q = \sum (y_i - \hat{y}_i)^2 = \sum (y_i - ax_i + b)^2 = \sum (y_i - w_1x_i + w_0)^2$$

$$\frac{\partial Q}{\partial \mathbf{w}} = \frac{\partial}{\partial \mathbf{w}} (\mathbf{y} - \mathbf{X}\mathbf{w})^2 = \frac{\partial}{\partial \mathbf{w}} (\mathbf{y}^T \mathbf{y} - 2\mathbf{w}^T \mathbf{X}^T \mathbf{y} + \mathbf{w}^T \mathbf{X}^T \mathbf{X} \mathbf{w}) = -2\mathbf{X}^T \mathbf{y} + 2\mathbf{X}^T \mathbf{X} \mathbf{w}$$

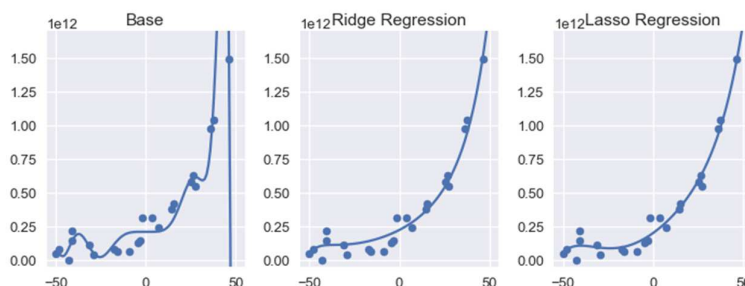
$$\frac{\partial Q}{\partial \mathbf{w}} \rightarrow 0$$

$$-2\mathbf{X}^T \mathbf{y} + 2\mathbf{X}^T \mathbf{X} \mathbf{w}$$

$$\mathbf{X}^T \mathbf{y} = \mathbf{X}^T \mathbf{X} \mathbf{w}, \mathbf{w} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

## Regression (4)

- Ridge regression
  - Error + L2 regularization



[https://www.textbook.ds100.org/ch/16/reg\\_lasso.html](https://www.textbook.ds100.org/ch/16/reg_lasso.html)

$$\frac{\partial Q}{\partial \mathbf{w}} = \frac{\partial}{\partial \mathbf{w}} ((\mathbf{y} - \mathbf{X}\mathbf{w})^2 + \lambda \|\mathbf{w}\|_2^2) \rightarrow 0$$

$$\mathbf{w} = (\mathbf{X}^T \mathbf{X} + \Gamma^T \Gamma)^{-1} \mathbf{X}^T \mathbf{y}, \Gamma = \alpha \mathbf{I}$$

- Lasso regression
  - Least absolute shrinkage and selection operator
  - Error + L1 regularization

$$+ \lambda \sum_{i=0}^n |w_i|$$

$$\lambda \frac{\partial}{\partial \mathbf{w}} (\|\mathbf{w}\|_1) = \lambda \sum \frac{\partial}{\partial w_i} (|w_i|)$$

$$\lambda \frac{\partial}{\partial w_i} (|w_i|) = \begin{cases} -\lambda & w_i < 0 \\ [-\lambda, \lambda] & w_i = 0 \\ \lambda & w_i > 0 \end{cases}$$

## Least Squares (1)

```
bool LeastSquared(double **X, double *w, double *y, int nRow, int nCol,
    bool bRidge, double alpha) {
    double **Xt = dmatrix(nCol, nRow);
    double **XtX = dmatrix(nCol, nCol);
    double **InverseXtX = dmatrix(nCol, nCol);
    double **PseudoInverseX = dmatrix(nCol, nRow);

    for(int r = 0 ; r < nCol ; ++r)
        for(int c = 0 ; c < nRow ; ++c)
            Xt[r][c] = X[c][r];

    for(int r = 0 ; r < nCol ; ++r)
        for(int c = 0 ; c < nCol ; ++c) {
            XtX[r][c] = 0;
            for(int k = 0 ; k < nRow ; ++k)
                XtX[r][c] += Xt[r][k] * X[k][c];

            if(bRidge)
                if(r == c) XtX[r][c] += alpha*alpha;
        }
}
```

$$\mathbf{w} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

## Least Squares (2)

```
if(InverseMatrix(XtX, InverseXtX, nCol)) {
    for(int r = 0 ; r < nCol ; ++r)
        for(int c = 0 ; c < nRow ; ++c) {
            PseudoInverseX[r][c] = 0;
            for(int k = 0 ; k < nCol ; ++k)
                PseudoInverseX[r][c] += InverseXtX[r][k] * Xt[k][c];
        }
    for(int r = 0 ; r < nCol ; ++r) {
        w[r] = 0;
        for(int k = 0 ; k < nRow ; ++k)
            w[r] += PseudoInverseX[r][k] * y[k];
    }
} else {
    free_dmatrix(Xt, nCol, nRow);
    free_dmatrix(XtX, nCol, nCol);
    free_dmatrix(InverseXtX, nCol, nCol);
    free_dmatrix(PseudoInverseX, nCol, nRow);

    return false;
}
```

$$\mathbf{w} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{y}$$

## Least Squares (3)

```
free_dmatrix(Xt, nCol, nRow);
free_dmatrix(XtX, nCol, nCol);
free_dmatrix(InverseXtX, nCol, nCol);
free_dmatrix(PseudoInverseX, nCol, nRow);
return true;
}
```

## Main.cpp (1)

```
...

class CLsmLayer : public CKhuGleLayer {
public:
    std::vector<CKhuGleSprite *> m_Point;
    bool m_bQuadricCurve;
    int m_nPointCnt;
    double **m_X, *m_y, *m_w;

    CLsmLayer(int nW, int nH, KgColor24 bgColor, CKgPoint ptPos = CKgPoint(0, 0),
        int nPointCnt = 100) : CKhuGleLayer(nW, nH, bgColor, ptPos) {
        m_X = nullptr;
        m_y = nullptr;
        m_w = nullptr;

        m_bQuadricCurve = true;

        GenerateData(nPointCnt, false);
    }
    virtual ~CLsmLayer() {
        if(m_X) free_dmatrix(m_X, m_nPointCnt, 3);
        if(m_y) delete [] m_y;
        if(m_w) delete [] m_w;
    }
    void GenerateData(int nCnt, bool bExtremeNoise);
};
```

## Main.cpp (2)

```
void CLsmLayer::GenerateData(int nCnt, bool bExtremeNoise) {
    if(m_X) free_dmatrix(m_X, m_nPointCnt, 3);
    if(m_y) delete [] m_y;
    if(m_w) delete [] m_w;

    m_nPointCnt = nCnt;
    m_X = dmatrix(m_nPointCnt, 3);
    m_y = new double[m_nPointCnt];
    m_w = new double[3];

    unsigned int seed
        = (unsigned int)std::chrono::system_clock
            ::now().time_since_epoch().count();
    std::default_random_engine generator(seed);
```

## Main.cpp (3)

```
std::uniform_real_distribution<double> uniform_dist1(0.005, 0.01);
std::uniform_real_distribution<double> uniform_dist2(m_nW*0.4, m_nW*0.6);
std::uniform_real_distribution<double> uniform_dist3(m_nH*0.9, m_nH*0.95);
std::uniform_real_distribution<double> uniform_dist4(m_nW*0.1, m_nW*0.9);
std::uniform_real_distribution<double> uniform_dist5(0, m_nW*0.1);
double a = -uniform_dist1(generator);
double x0 = uniform_dist2(generator);
double y0 = uniform_dist3(generator);
double ExtremeNoisePos = uniform_dist4(generator);
```

## Main.cpp (4)

```
for(auto &Child : m_Children)
    delete Child;
m_Children.clear();
m_Point.clear();

double x, y, noise;
double m = (rand()%2?1:-1)*a*100;
for(int i = 0 ; i < m_nPointCnt ; ++i) {
    noise = uniform_dist5(generator)-m_nW*0.05;
    x = uniform_dist4(generator);

    if(m_bQuadricCurve)    y = a*(x-x0)*(x-x0) + y0 + noise;
    else    y = m*(x-x0) + y0 + noise;

    if(bExtremeNoise) {
        if(x > ExtremeNoisePos-m_nW*0.05 && x < ExtremeNoisePos+m_nW*0.05) {
            if(m_bQuadricCurve)
                y = a*(x-x0)*(x-x0) + y0 + (noise-m_nW*0.05)*3;
            else
                y = m*(x-x0) + y0 + (noise-m_nW*0.05)*3;
        }
    }
}
```

## Main.cpp (5)

```
m_X[i][0] = x*x;
m_X[i][1] = x;
m_X[i][2] = 1;

m_y[i] = y;

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, 200, 255), false, 30);

m_Point.push_back(Point);
AddChild(Point);
}
SetBackgroundImage(m_nW, m_nH, m_bgColor);
}

class CRegression : public CKhuGleWin {
public:
    CLsmLayer *m_pLsmLayer;

    CRegression(int nW, int nH);
    void Update();
};
```

## Main.cpp (6)

```
CRegression::CRegression(int nW, int nH) : CKhuGleWin(nW, nH) {
    m_pScene = new CKhuGleScene(640, 480, KG_COLOR_24_RGB(100, 100, 150));
    m_pLsmLayer = new CLsmLayer(400, 400, KG_COLOR_24_RGB(150, 150, 200),
        CKgPoint(120, 40), 200);
    m_pScene->AddChild(m_pLsmLayer);
}
void CRegression::Update() {
    if(m_bKeyPressed['Q']) {
        m_pLsmLayer->m_bQuadricCurve = !m_pLsmLayer->m_bQuadricCurve;
        m_pLsmLayer->GenerateData(200, false);
        m_bKeyPressed['Q'] = false;
    }
}
```

## Main.cpp (7)

```
if(m_bKeyPressed['S']) {
    LeastSquared(m_pLsmLayer->m_X, m_pLsmLayer->m_w, m_pLsmLayer->m_y,
        m_pLsmLayer->m_nPointCnt, 3, false, 0);

    int y0;
    for(int x = 0 ; x < m_pLsmLayer->m_nW ; ++x) {
        int y = (int)(m_pLsmLayer->m_w[0]*x*x + m_pLsmLayer->m_w[1]*x
            + m_pLsmLayer->m_w[2]);
        if(x > 0) {
            CKhuGleSprite::DrawLine(m_pLsmLayer->m_ImageBgR,
                m_pLsmLayer->m_ImageBgG, m_pLsmLayer->m_ImageBgB,
                m_pLsmLayer->m_nW, m_pLsmLayer->m_nH, x-1, y0,
                x, y, KG_COLOR_24_RGB(255, 0, 0));
        }
        y0 = y;
    }
}
```



## Main.cpp (8)

```
LeastSquared(m_pLsmLayer->m_X, m_pLsmLayer->m_w, m_pLsmLayer->m_y,
             m_pLsmLayer->m_nPointCnt, 3, true, 0.9);

for(int x = 0 ; x < m_pLsmLayer->m_nW ; ++x) {
    int y = (int)(m_pLsmLayer->m_w[0]*x*x + m_pLsmLayer->m_w[1]*x
                 + m_pLsmLayer->m_w[2]);
    if(x > 0) {
        CKhuGleSprite::DrawLine(m_pLsmLayer->m_ImageBgR,
                                m_pLsmLayer->m_ImageBgG, m_pLsmLayer->m_ImageBgB,
                                m_pLsmLayer->m_nW, m_pLsmLayer->m_nH, x-1, y0, x, y,
                                KG_COLOR_24_RGB(255, 255, 0));
    }
    y0 = y;
}
m_bKeyPressed['S'] = false;
}
```

## Main.cpp (9)

```
if(m_bKeyPressed['N'] || m_bKeyPressed['M']) {
    if(m_bKeyPressed['M']) m_pLsmLayer->GenerateData(200, true);
    else m_pLsmLayer->GenerateData(200, false);

    m_bKeyPressed['N'] = false;
    m_bKeyPressed['M'] = false;
}
m_pScene->Render();

if(m_pLsmLayer->m_bQuadricCurve)
    DrawSceneTextPos("Regression: quadric curve", CKgPoint(0, 0));
else
    DrawSceneTextPos("Regression: line", CKgPoint(0, 0));
CKhuGleWin::Update();
}

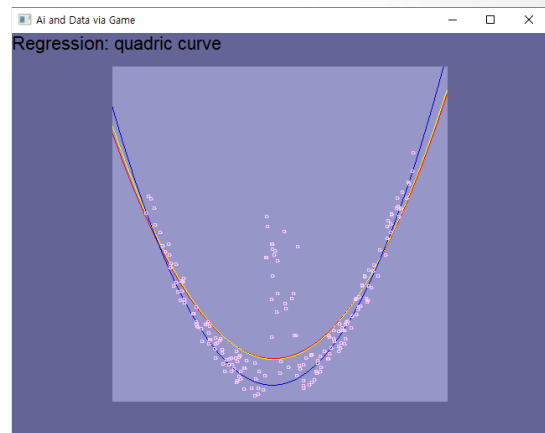
int main() {
    CRegression *pRegression = new CRegression(640, 480);
    KhuGleWinInit(pRegression);
    return 0;
}
```

# Practice VI

- RANSAC (Random sample consensus)
  - Iterative parameter estimation method

```

•  $\mathbf{W} \leftarrow \emptyset$ 
   $C_M \leftarrow 0$ 
  while iteration do
    randomly subset selection
    estimate parameter ( $\mathbf{W}_i$ )
    inlier count ( $C_i$ )
    if  $C_i > C_M$  then
       $C_M \leftarrow C_i$ 
       $\mathbf{W} \leftarrow \mathbf{W}_i$ 
    end if
  end while
    
```

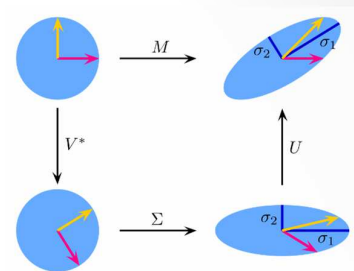


## Advanced Courses (1)

- Singular value decomposition (SVD)

$$\mathbf{M} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T$$

- $\mathbf{U}$  and  $\mathbf{V}$  are singular vectors, orthonormal and unitary matrices
- $\mathbf{\Sigma}$  is a diagonal matrix having singular values
- Applications
  - Pseudo inverse
  - Truncated SVD
    - Regularization
    - Dimensionality reduction



$$\mathbf{M} = \mathbf{U} \cdot \mathbf{\Sigma} \cdot \mathbf{V}^*$$

<https://upload.wikimedia.org/wikipedia/commons/thumb/b/bb/Singular-Value-Decomposition.svg/220px-Singular-Value-Decomposition.svg.png>

- Logistic regression
  - Classification using a logistic function

$$P(y=1) = \frac{1}{1 + e^{-(b+\mathbf{w}\mathbf{X})}}$$

$$\frac{1}{P(y=1)} - 1 = e^{-(b+\mathbf{w}\mathbf{X})}, \quad \frac{1 - P(y=1)}{P(y=1)} = \frac{1}{e^{(b+\mathbf{w}\mathbf{X})}}$$

$$\log\left(\frac{P(y=1)}{1 - P(y=1)}\right) = \log\left(\frac{P(y=1)}{P(y=0)}\right) = b + \mathbf{w}\mathbf{X}$$

