English Version:

XSX:

To estimate the probability of previously non-award-winning countries securing a medal in the next Olympic Games, we employed a neural network to learn a classifier that predicts whether a country without a medal in the current games will win a medal in the next. The constructed network consists of four layers: one input layer, two hidden layers, and one output layer. The input layer includes three features, the two hidden layers contain four and three neurons, respectively, and the output layer comprises a single neuron representing the probability of winning a medal in the next games.

The sigmoid function served as the activation function, while gradient descent optimized the propagation matrix parameters ($\Theta_{jk}^{(i)} := \Theta_{jk}^{(i)} - \eta\frac{\partial J}{\partial\Theta_{jk}^{(i)}}$) to minimize the loss function $J(\Theta) = -\frac{1}{n}\sum_{i=1}^{n}[y^{(i)}log(\hat{y}^{(i)}) + (1-\hat{y}^{(i)})]$. The backpropagation algorithm was used to calculate the gradient of each element in the propagation matrices during optimization. Finally, the accuracy on the validation set and the value of the loss function were used to assess the classifier's predictive performance and ensure its reliability.

LNY:

To demonstrate evidence of the existence of the ‘great coach’ effect, we set the weighted medal count as $W_t = 3 \times Gold_t + 1 \times Silver_t + 1 \times Bronze_t$, assuming that W_t has different distributions before and after the year of the change and that W_t in each interval obeys a normal distribution. Bayesian change point detection is used to identify change points in the time series data. Then, we determine whether the change points are caused by the ‘great coach’ effect by combining the last year of the ‘great’ coach. After that, we calculate the coach's contribution rate by comparing the changes in the number of medals before and after the change point.

Next, based on the countries and their sports where there are ‘great’ coaches, we calculate the historical level of a country in a certain sport as follows:
$Level = 4 \times Gold_t + 3 \times Silver_t + 1 \times Bronze_t + 0.5 \times No\ Medal_T$.
By analyzing the historical level and the total number of medals in the sport, we can select a country to be the best in the world. The total number of medals in the program, three countries, and their sports that should be considered for investment in ‘great’ coaches were selected. Finally, an attempt was made to build a regression model of coaching contribution, historical level, and number of medals in the sport to predict the contribution of the ‘great coach’ effect to the number of medals in these three countries.

中文翻译：

XSX:

为了得到未得奖过的国家下一届拿奖的概率，我们尝试通过神经网络学习得到此届未拿奖，下一届是否拿奖的分类器。建立一个层数为4，其中输入层与输出层各一个，隐藏层2个。其中输入层有3个特征，2个隐藏层分别有4个，3个神经元，输出层只有一个神经元，表示下一届拿奖的概率。并使用sigmoid函数作为激活函数，通过梯度下降法优化传播矩阵参数($\Theta_{jk}^{(i)} := \Theta_{jk}^{(i)} - \eta\frac{\partial J}{\partial\Theta_{jk}^{(i)}}$)使得损失函数

$J(\Theta)=-\frac{1}{n}\sum_{i=1}^{n}[y^{(i)}log(\hat{y}^{(i)})+(1-\hat{y}^{(i)})]$ 最小化最终得到分类器，在优化过程中使用了反向传播法得到每个传播矩阵上每个元素的梯度。最终通过验证集的正确率与损失函数值验证了分类器分类的正确性。

LNY:

为了证明"伟大教练"效应存在的证据，我们设置加权奖牌数为：
$W_t=3\times Gold_t+1\times Silver_t+1\times Bronze_t$ ，
假设 W_t 在变化年份前后具有不同的分布，并且每个区间内的 W_t 服从正态分布。采用贝叶斯变化点检测方法，识别时间序列数据中的变化点。然后结合"伟大"教练的上任年份，判断变化点是否由"伟大教练"效应引起。之后，我们通过比较变化点前后的奖牌数变化来计算教练的贡献率。

接下来，根据我们得到的存在"伟大"教练的国家及其运动项目，计算某个国家在某个项目上的历史水平，公式如下：
$Level=4\times Gold_t+3\times Silver_t+1\times Bronze_t+0.5\times No\ Medal_T$ 。
通过分析历史水平和项目的奖牌总数，挑选出三个国家及其应考虑投资于"伟大"教练的运动项目。最后，尝试建立教练贡献率、历史水平和项目奖牌数的回归模型，以预测"伟大教练"效应对这三个国家奖牌数的贡献率。