The Future of Work:

Machine Learning and Employment

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Abstract

The goal of the project is to build upon the work of Frey & Osborne [1] about the future of employment and further investigates how susceptibilities of jobs has affected employment since 1980s. Machine learning techniques are applied to two sets of data, each containing a list of job descriptors from 1977 and 2010 respectively, to estimate the probability of computerisation for every occupation in each time period. These estimations are then examined on labor force market changes. The result proves the conclusion of many others work [2], from a probability point of view, that computer capital is substitutive for jobs involving routine tasks – tasks following specific rules, but not a threaten to jobs involving non-routine tasks in general, although there are indications that some non-routine jobs such as non-routine manual jobs are no longer safe.

Acknowledgement

First I would like to thank my supervisor, Michael Osborne, for his generous support throughout this project. His patient advices as well as his brilliant lectures have all helped me understanding the subject and finishing the project. I would also like to thank Carl Frey from Oxford Martin School for his invaluable advices on the use of employment data that forms the core data source of my experiments. Finally, I would like to acknowledge the reference of GP regression code written by Mark Ebden, where I started developing my own GP program.

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Chapter 1

Introduction

The question of how technology could influence employment has been a popular issue for quite a long time [3]. Since 1990s, it was believed that technological changes have favoured the more skilled workers while reduced the demand for less skilled workers [4]. Nowadays, with much faster development of technologies especially in automation technology, it is very likely for people to believe that less human worker is required. If it is true, could it be the major cause for lower employment rate? Will the development of technology make more people jobless? Or is it just a temporary phenomenon?

Many works have been done to reveal the impact of technology on labor force. Brynjolfsson and McAfee [5] believed that technology has contributed to persistent high employment rate. They observed that, after the Great Recession[1], when companies are expected to take in more workers, they bought more computers. The only reason behind is that computer capital became cheaper than human worker.

Although it is commonly believed that there are jobs in which human is not replaceable [6], there are large amount of jobs that have already been automated. Past works have proven

[1] A period of economic decline observed in world markets during the late 2000s

that computers are substitutive for jobs mainly involving routine tasks [2]. However, with recent development in artificial intelligence such as pattern recognition, some non-routine tasks, especially non-routine manual tasks are no longer invincible. It is not impossible that other non-routine tasks would be manageable by computers in the future.

In this project, GP is run on two sets of data, one includes variables related to 2010 occupations, the other includes tasks performed for each occupation in 1977 [2]. The training set of 2010 occupations are hand-labeled data from the workof Frey & Osborne [1]. The same labels are transferred to 1990 occupations through official crosswalk files from IPUMS [7], [8] [9]. These two sets of data are run with GP classification MATLAB program separately. The results are then compared with each other as well as with historical labor force data [10].

The following chapters will present the details of how machine learning is used for studying the relation between technology development and employment. Chapter 2 will introduce the basics of the Gaussian process and the implementation details of Gaussian process classification. Then Chapter 3 will be talking about how employment data sets from 2010 and 1980 are used in GP and what conclusions could we make from the results. Finally Appendix A includes some numerical results of the project.

Chapter 2

Gaussian Process

Gaussian Process(GP) is a modelling method in which all variables are assumed to follow normal distribution. Any finite combination of input spaces also has a joint Gaussian distribution. Thus the distribution of a Gaussian Process model can be seen as the infinite-dimensional generalization of multivariate normal distribution.

Gaussian Process has several advantages over other models. First, its non-parametric modelling process gives the maximum flexibility. It is not restricted by any pre-defined parameters. Second, Gaussian Process is particularly useful for small data sets because the prescence of hyper-parameters gives it characteristics you want (such as smoothness and periodicity), at the same time keeping a fine fit to the data.

By definition, a Gaussian Process $f(x)$ is specified by a mean function and a covariance function, denoted as

$$f(x) \sim GP(\mu(x), K(x,x))$$

where

$$\mu(x) = \mathbb{E}(f(x)) \tag{2.1}$$

$$k(x, x\prime) = \mathbb{E}((f(x) - \mu(x)(f(x\prime) - \mu(x\prime)) \tag{2.2}$$

Both the mean and covariance function are the choice of user and can have crucial effects on the final Gaussian process distribution.

To describe how all the input points are related together we use the covariance matrix defined as

$$K(x, x\prime) = \begin{bmatrix} k(x_1, x_1) & k(x_1, x_2) & \cdots & k(x_1, x_n) \\ k(x_2, x_1) & k(x_2, x_2) & \cdots & k(x_2, x_n) \\ \vdots & \vdots & \ddots & \vdots \\ K(x_n, x_1) & k(x_n, x_2) & \cdots & k(x_n, x_n) \end{bmatrix} \tag{2.3}$$

Mean Function

The prior mean function $\mu(x)$ describes the beliefs in output y(x) before any observations are made. The most popular choices of μ includes 0 and other constants. More complicated mean functions can be defined by using certain parameters based on domain knowledge. However, one should always be careful in selecting the mean function since it is what our inference is extrapolated from.

Covariance Function

Many characteristics such as smoothness, stationarity, and periodicity can be integrated in covariance function. It describes how individual observations are related to each other. In reverse, learning in Gaussian Process also defines the properties of covariance function, giving us the model that can be used for upcoming predictions.

One common choice is the squared exponential covariance function

$$k(x, x\prime) = \sigma_f^2 \exp\left[-\frac{(x - x\prime)^2}{2l^2}\right]$$

where l is the lengthscale representing how far a certain training point could affect the predictions. It is suitable for smooth data. One thing to notice is that the $k(x, x\prime)$ is actually the covariance between y and $y\prime$, corresponding to the output of x and $x\prime$ respectively. Other covariance functions such as rational quadratic function can be useful for data that is smooth over a range of length scales.

Matérn class of covariance functions is another important branch of covariance functions. They take the form of

$$K_{Matrn}(x, x\prime) = \lambda^2 \frac{2^{1-\nu}}{\Gamma(\nu)} \left(\frac{\sqrt{2\nu} d(x, x\prime)}{l}\right)^{\nu} K_{\nu}\left(\frac{\sqrt{2\nu} d(x, x\prime)}{l}\right)$$

where $d(x, x\prime)$ is the distance between x and $x\prime$. This type of covariance is normally used for functions of varying smoothness.

Periodicity can be added by using the periodic covariance of the form

$$K_P(x, x\prime) = \lambda^2 \exp\left(-\frac{2sin^2\left(\pi d(x, x\prime)/\rho\right)}{\omega}\right)$$

where ρ determines the period and ω gives the roughness.

Covariance functions can be combined to give multi-character correlations. For example, if we know that it requires both periodicity and smoothness in the distribution, the multiplication of squared exponential function and periodic function can be used. If the prior information is that either periodicity or smoothness exists, the addition of the above two functions suits better. Similar techniques can be applied to distributions that are known to be the sum of independent functions or the product of independent functions.

One thing to notice is that most of the covariance functions involves computing the distance between input points. This distance could either simply be the euclidean distance $d_E(x, x\prime) = \sqrt{\sum_{i=1}^{n}(x_i - x_i\prime)^2}$ or the weighted distance defined by $d_w(x, x\prime) = \sqrt{\sum_{i=1}^{n}\frac{(x_i - x_i\prime)^2}{w_i^2}}$

2.1 Gaussian Process Regression

GP Regression by its name is the process of finding a model to fit a data set using Gaussian Process. In practice, it is often the case that the output data we collected are noise corrupted. eg. $y = f(x) + \epsilon$. If we assume the noise is Gaussian with variance σ_n^2 and independent in each observation, covariance between observations then becomes

$$\mathrm{cov}(y, y\prime) = k(x, x\prime) + \sigma_n^2\delta \tag{2.4}$$

where δ is the Kronecker delta function which becomes 1 when $x = x\prime$ and 0 otherwise.

2.1.1 MLE and MAP for Setting Hyperparameters

Although Gaussian Process is non-parametric, we still need to find the hyperparameters which define the mean and covariance functions. In fact, the objective of finding hyperparameters

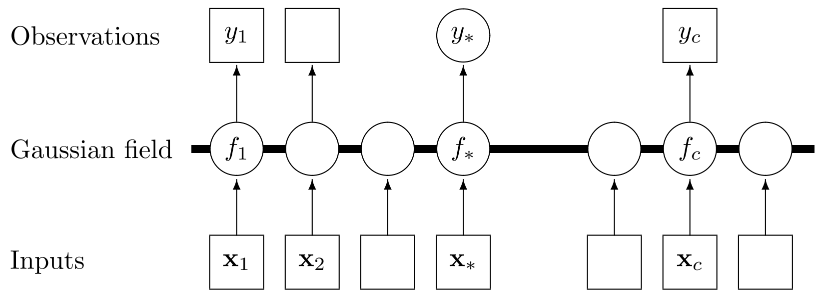


Figure 2.1: The relation between input (x), observational output (y), and the latent variable (f). Figure from [11]

other than the parameters for model itself gives us more freedom in defining the distribution function.

According to Baye's rule,

$$\text{posterior} = \frac{\text{likelihood} \times \text{prior}}{\text{marginal likelihood}}$$

if θ is the collection of all hyperparameters

$$p(\theta|X, y) = \frac{p(y|X, \theta)p(\theta)}{p(y|X)}$$

where the marginal likelihood $p(y|X)$ is given by

$$p(y|X) = \int p(y|X, \theta)p(\theta)d\theta \tag{2.5}$$

The MLE and MAP estimates the integrals by approximating the likelihood $p(y|X, \theta)$ and posterior $p(\theta|X, y)$ respectively as delta function of θ. Indeed, the differences between the approximation and the real function value may have an negative impact on our final results. However, as the approximations are on hyperparameters, which only affects mean and covariance function but not the function parameters (function values), the negative impact arisen from

MLE or MAP is reduced as they propagate to the actual function values.

Note that in equation (2.5), θ is marginalised out therefore $p(y|X)$ is independent of the values of theta. The maximum a posterior estimate of θ happens when $p(\theta|X, y)$ is maximised. Since $p(\theta|X, y)$ is proportional to $p(y|X, \theta)$, if we have little knowledge about the prior information of θ, finding the maximum of the posterior is equivalent to obtaining the value of θ that maximises $p(y|X, \theta)$. $p(y|X, \theta)$ can be written as the integration of latent variable f

$$p(y|X, \theta) = \int p(y|f, X, \theta)p(f|X, \theta)df \tag{2.6}$$

In Gaussian Process model we assume that $p(f|X, \theta)$ is a Gaussian with mean 0 and variance K. A multi-variate Gaussian probability density function can be written as

$$\mathcal{N}(\mathbf{x}, \mu, \mathbf{\Sigma}) = \frac{1}{\sqrt{|2\pi\mathbf{\Sigma}|}} \exp\left(-\frac{1}{2}(\mathbf{x} - \mu)^T \mathbf{\Sigma}^{-1}(\mathbf{x} - \mu)\right)$$

therefore we have

$$\log p(f|X, \theta) = -\frac{1}{2} f^T K^{-1} f - \frac{1}{2} \log |K| - \frac{n}{2} \log 2\pi \tag{2.7}$$

also we know that $y|f \sim \mathcal{N}\left(f, \sigma_n^2 I\right)$, combining it with the above equation we get

$$\log p(y|X, \theta) = -\frac{1}{2} y^T (K + \sigma_n^2 I)^{-1} y - \frac{1}{2} \log \left|K + \sigma_n^2 I\right| - \frac{n}{2} \log 2\pi \tag{2.8}$$

This is the final objective function to be maximised. The covariance of y from this equation is $K + \sigma_n^2$, which is also consistent with the covariance of y we derived earlier in equation (2.4) where a noise term is added to the diagonal of K.

2.1.2 Predictions

After finding the optimised hyperparameters, predictions can be made by substituting the new inputs into the Gaussian Process model defined by mean and covariance function with the optimised parameters. The joint distribution of training data with no noise can be written as

$$\begin{bmatrix} \mathbf{f} \\ \mathbf{f}_* \end{bmatrix} \sim \mathcal{N}\left(\mu(X), \begin{bmatrix} K(X,X) & K(X,X_*) \\ K(X_*,X) & K(X_*,X_*) \end{bmatrix}\right) \tag{2.9}$$

Where $\mathbf{f}_*$ denotes the predictions in f domain. Similarly, distribution of noisy training data can be expressed as

$$\begin{bmatrix} \mathbf{y} \\ \mathbf{f}_* \end{bmatrix} \sim \mathcal{N}\left(\mu(X), \begin{bmatrix} K(X,X)+\sigma_n^2 I & K(X,X_*) \\ K(X_*,X) & K(X_*,X_*) \end{bmatrix}\right) \tag{2.10}$$

Then the distribution of $\mathbf{f}_*$ conditioned on X, X_* and $\mathbf{f}$ follows a Gaussian with mean and variance as below

$$\bar{\mathbf{f}}_* = \mu(X_*) + K(X_*,X)K(X,X)^{-1}(\mathbf{f} - \mu(X)) \tag{2.11}$$

$$\mathrm{cov}(\mathbf{f}_*) = K(X_*,X_*) - K(X_*,X)K(X,X)^{-1}K(X,X_*) \tag{2.12}$$

and the noisy version,

$$\bar{\mathbf{f}}_* = \mu(X_*) + K(X_*,X)[K(X,X)+\sigma_n^2 I]^{-1}(\mathbf{y} - \mu(X)) \tag{2.13}$$

$$\mathrm{cov}(\mathbf{f}_*) = K(X_*,X_*) - K(X_*,X)[K(X,X)+\sigma_n^2 I]^{-1}K(X,X_*) \tag{2.14}$$

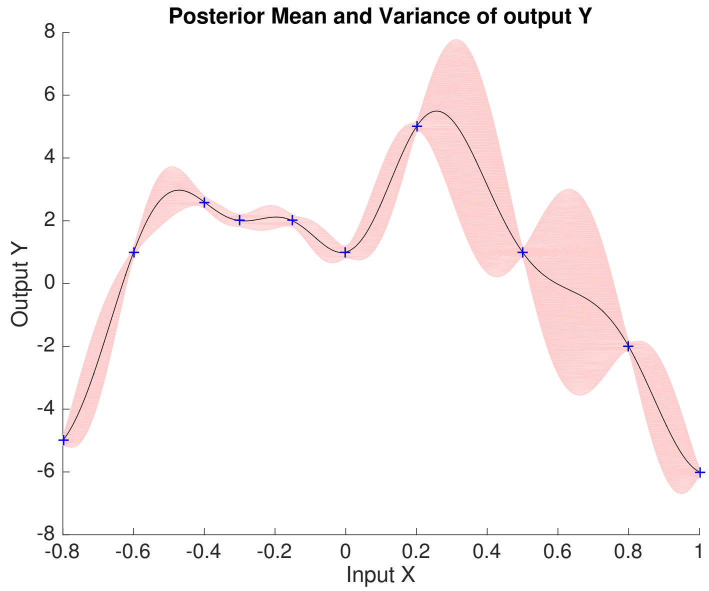


Figure 2.2: Example plot of Regression with 1D input and output. Blue points represent the training set. Red region represents the variance of prediction. Note that the variance at the training points is almost reduced to zero as there is little uncertainty at these points (they are actually zero in noise free cases). The further way from training points, the more uncertain predictions become.

2.1.3 Computational Issues

Conditioning on Covariance Matrix

Covariance matrix K has to be positive semi-definite for its consequencial steps to be numerically stable. However, when the input data is so closed to each other compared to the length scale used, adjacent rows in K might become the same under limited significant figures, making the matrix not full rank anymore.

This problem is avoided in regression problems by adding noise. While in classification problems that we are going to talk about later, artificial noise, also called jitters, has to be added. The amount of jitters needed differs by data, and user is required to adjust its size until K becomes positive definite.

Cholesky Decomposition

For large data sets, Gaussian Process can be very slow. The computation on large covariance matrix makes it highly time consuming. The most expensive computation is the inversion of K. Cholesky decomposition is one way to tackle this problem. It decomposes a positive definite matrix into product of two triangular matrices

$$K = LL^T = U^T U \tag{2.15}$$

where L is a lower triangular matrix and U is an upper triangular matrix. The inverse of K can simply be computed by

$$K^{-1} = L^{-T} L^{-1} = U^{-1} U^{-T} \tag{2.16}$$

It is much faster to compute the inverse of a triangular matrix, giving a reduction in computation complexity from $\mathcal{O}(n^3)$ to $\mathcal{O}(\frac{1}{3}n^3)$ [12]. In addition, matrix inversion based on cholesky decomposition is more numerically stable.

Partial Derivatives of Hyperparameters

To optimise the hyperparameters using Newton's method, we need to compute the gradients of log likelihood of θ wrt. the hyperparameters θ_i, given by

$$\begin{aligned}\frac{\partial}{\partial \theta_i} \log p(y|X,\theta) &= \frac{1}{2} y^T K^{-1} \frac{\partial K}{\partial \theta_i} K^{-1} y \; - \; \frac{1}{2} tr(K^{-1} \frac{\partial K}{\partial \theta_i}) \\ &= \frac{1}{2} tr\big((\alpha\alpha^T - K^{-1}) \frac{\partial K}{\partial \theta_i}\big) \qquad \text{where} \quad \alpha = K^{-1} y\end{aligned} \tag{2.17}$$

One thing to notice is that many of the parameters, such as lengthscale and frequency, are always positive. Therefore it is more convenient to optimise over their logrithms other than themselves. e.g $\theta = \log\theta$

2.2 Gaussian Process Classification

Gaussian Process classification can be simply derived from GP regression except for the fact that outputs are discrete numbers representing class labels instead of continuous numbers in regression. Typically class labels are 1 and -1 for binary class problems. However, we do get a continuous intermediate function before the final label is decided. This is the latent variable on which regression is applied. Then the result of regression will be 'squashed' into range [0,1] to give the probability of a certain class.

2.2.1 The 'Squashing' Function

The 'squashing' function can be any sigmoid function. Two typical sigmoid functions are logistic function $\lambda(f) = 1/(1+\exp(-y_i f_i))$ and cumulative Gaussian function $\Phi(f)$. Inference is hence divided into two steps. First is to compute the distribution of the prediction latent variable f_* in terms of previous observations

$$p(\boldsymbol{f}_*|\boldsymbol{X}, \boldsymbol{y}, \boldsymbol{x}_*) = \int p(\boldsymbol{f}_*|\boldsymbol{X}, \boldsymbol{x}_*, \boldsymbol{f})p(\boldsymbol{f}|\boldsymbol{X}, \boldsymbol{y})\ d\boldsymbol{f} \tag{2.18}$$

where $p(\boldsymbol{f}|\boldsymbol{X}, \boldsymbol{y}) = p(\boldsymbol{y}|\boldsymbol{f})p(\boldsymbol{f}|\boldsymbol{X})/p(\boldsymbol{y}|\boldsymbol{X})$ is the posterior of latent variables $\boldsymbol{f}$, which is estimated by MAP with respect to hyperpamaters(l and σ_f).

Then the probabilistic prediction is estimated by substitute the latent f into sigmoid function and average over

$$\bar{\pi}_* \triangleq p(y_* = +1|X, y, x_*) = \int \sigma(f_*) p(f_*|X, y, x_*) df_* \tag{2.19}$$

2.2.2 The Laplace Approximation

In the case of regression (equation 2.6), we assumed that both the likelihood $p(y|f)$ and the posterior over latent variable $p(f|X, \theta)$ are Gaussian. The integral for finding $p(y|X, \theta)$ and the prediction can be computed analytically. However, in classification, the non-Gaussian likelihood and the posterior of latent function make the integral (equation (2.18)) not analytically tractable. Laplace's approximation can be used to approximate these two terms by doing a second order Taylor expansion around its maximum point.

The Gaussian approximation of the posterior of f can be obtained by:

$$q(f|X, y) = \mathcal{N}(f|\hat{f}, A^{-1}) \propto \exp(-\frac{1}{2}(f - \hat{f})^T A(f - \hat{f})) \sim p(f|X, y) \tag{2.20}$$

where $\hat{f} = \mathrm{argmax_f}\, p(f|X, y)$ and $A = -\bigtriangledown \bigtriangledown \log p(f|X, y)|_{f=\hat{f}}$ is the hessian of negative log posterior.

The reason we choose Laplace's approximation here is that it is more likely to give a better approximation than MLE or MAP [13]. Although it may still be inappropriate for the true shape of the data: the peak can be much sharper or flatter than what the approximation described.

2.3 Implementation

2.3.1 Optimising the latent variable

By Baye's rule

$$p(\boldsymbol{f}|\boldsymbol{X}, \boldsymbol{y}) = p(\boldsymbol{y}|\boldsymbol{f})p(\boldsymbol{f}|\boldsymbol{X})/p(\boldsymbol{y}|\boldsymbol{X})$$

We need to find the $\hat{f}$ that maximises $p(f|X, y)$. Also, $p(y|X)$ is independent of f, only the numerator need to be considered. Take the logrithm of $p(f|X, y)$ we get

$$\begin{aligned}\Psi(f) &= \log p(f|X, y) \\ &= \log p(y|f) + \log p(f|X) \\ &= \log p(y|f) + \frac{1}{2}f^T K^{-1} f - \frac{1}{2}\log|K| - \frac{n}{2}\log 2\pi\end{aligned} \tag{2.21}$$

and its derivatives w.r.t. f:

$$\nabla\Psi(f) = \nabla \log p(y|f) - K^{-1}f \tag{2.22}$$

$$\nabla\nabla\Psi(f) = \nabla\nabla \log p(y|f) - K^{-1} = -W - K^{-1} \tag{2.23}$$

where W is the second derivative of negative log likelihood of f. Since we know that y_i depends on f_i only, W is a diagonal matrix. The best latent f can then be found at $\nabla\Psi = 0$, which gives

$$\hat{f} = K(\nabla \log p(y|\hat{f})) \tag{2.24}$$

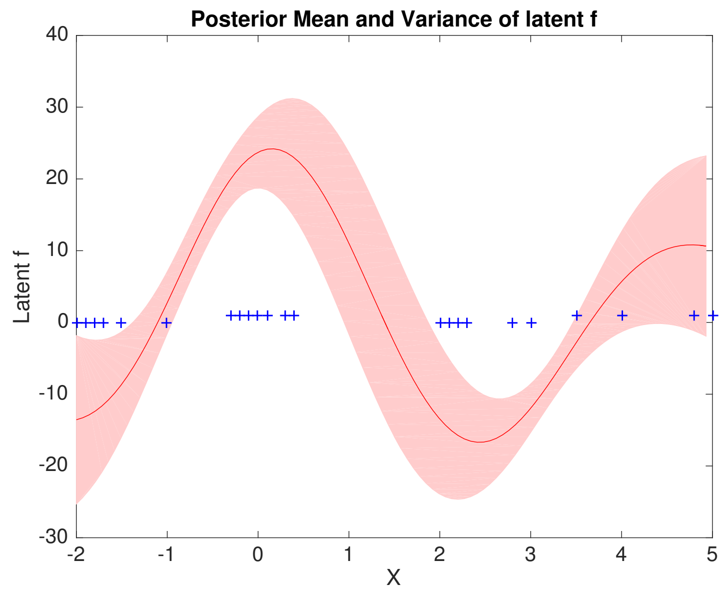


Figure 2.3: Example plot of latent variable. Blue crosses are training points and red region is its variance. The variance now is never going to be zero because the latent function value is not told directly. While in noise free regression, the exact value of output at training points is told.

This is a non-linear function therefore can be solved by Newton's method. Commonly used convergence criteria include the difference between successive values of $\Psi(f)$, the magnitude of gradient vector $\nabla\Psi(f)$ or the changes between values of f. In practice, the convergence of objective function is assured by checking that each iteration gives an increase in $\Psi(f)$. If not, a smaller step change in f should be used.

2.3.2 Maximising the Objective Function

The objective function here is the log posterior $p(y|X,\theta) = \int p(y|f)p(f|X)df = \int \exp(\Psi(f))df$ which can be obtained by using Laplace's approximation of $p(f|X,y)$ (Taylor expansion around $\hat{f}$)

$$p(y|X,\theta) \simeq q(y|X,\theta) = exp(\Psi(\hat{f}))\int \exp(-\frac{1}{2}(f-\hat{f})A(f-f\hat{f}))df \tag{2.25}$$

thus

$$\log q(y|X,\theta) = -\frac{1}{2}\hat{f}^T K^{-1}\hat{f} + \log p(y|\hat{f}) - \frac{1}{2}\log|B| \tag{2.26}$$

where $|B| = |I_n + W^{\frac{1}{2}}KW^{\frac{1}{2}}|$ and K is covariance defined by θ. This is the final function we need to run optimisation on.

Sampling Methods for Hyperparameters

In most of the cases, the objective function is non-linear, which means that more than one set of initial hyperparameters has to be assigned as the starting points for optimisation. Following are two methods used for low number of hyperparameters (usually 1 or 2) and higher number of hyperparameters.

Uniform sampling is one of the most common and easily obtainable sampling method. Samples are simply drawn from sample space by dividing the sample space with the number of required samples and taking one in each subspaces (or more strictly, with equal distance between samples). This is usually an idea sampling method for low dimensional problems where the number of dimensions will not largely increase the number of samples if we want to achieve the same number of sampling intervals in each dimension.

Latin Hypercube Sampling (LHS) [14] is commonly used for higher dimensional problems. If we want N samples from a one-dimensional variable, we can either uniformly take N points with equal distant from one another, or we can divide the sampling space into N equal intervals and take one sample from each interval. LHS is a simple extension from uniform sampling. When taking N samples from a M-dimensional variable, the sampling space of each dimension is divided into N equal intervals. Each interval is sampled once with the order of sampling being random. Then all the samples from M dimensions are combined to give N samples each has

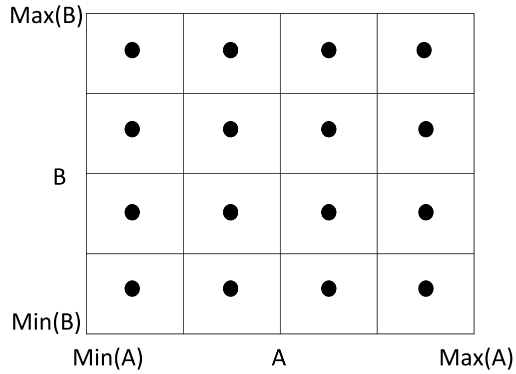
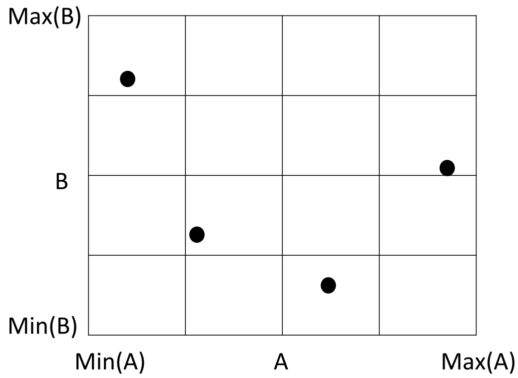


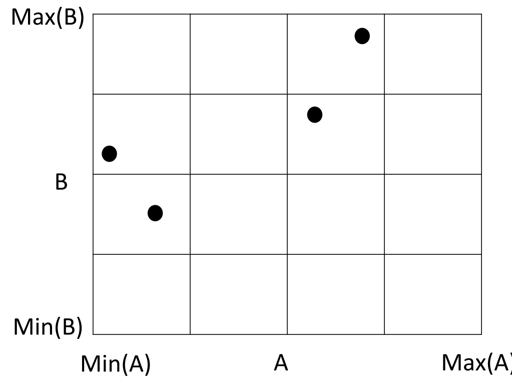
Figure 2.4: A simple example of 2-dimensional uniform sampling with 4 sampling intervals in each dimension.

M dimensions. Each of the possible combinations of intervals forms a multi-dimensional region that sample could draw from, called a Latin square for two-dimensional sampling space and a Latin hypercube for higher dimensions.

One advantage of LHS over random sampling is its uniformity. It ensures that samples are well-distributed in each dimension independently. While in random sampling, samples are generated without taking into account the previous samples, they results may be squeezed together, resulting in repeated optimisation results while leaving the other area blank. Non-linear function optimisation means that samples has to be well distributed. The more uniform the samples are, the more likely the global maximum could be found. Another important feature is that LHS does not require more samples for larger dimensions. In uniform sampling, a M-dimensional variable with N samples for each dimension means that N$\times$M samples will be drawn in order to cover the whole sampling space. Obviously for higher dimensional problems this is too time-consuming. For Gaussian process, the hyperparameters involved in optimisation include those used to define mean and covariance functions. When each weighting computing the distance between inputs are treated as hyperparameters, much higher dimensional samples needs to be drawn, leading to a strong preference in Latin Hypercube Sampling.



(a) Latin Hypercube Sampling



(b) Random Sampling

Figure 2.5: Comparison between Latin Hypercube sapling and random sampling. Although Latin hypercube sampling may not represent the most variable overall (which can be improved by Orthogonal sampling), it gives a pretty good variability in each dimension. Random sampling does not secure any variability.

Derivatives of Hyperparameters

Again, as in regression, we need to find the gradient of likelihood w.r.t. all the hyperparameters we are trying to optimise. The case is slightly more difficult than regression as we introduced a latent variable f and used Laplace's Approximation for likelihood itself.

Since covariance matrix K is a function of hyperparameters, therefore $\hat{f}$ and W are implicit functions of hyperparameters. The derivative of equation (2.20) is

$$\frac{\partial \log q(y|X,\theta)}{\partial \theta_i} = \frac{\partial \log q(y|X,\theta)}{\partial \theta_i}\Big|_{explicit} + \sum_{i=1}^{n} \frac{\partial \log q(y|X,\theta)}{\partial \hat{f}_i} \frac{\partial \hat{f}_i}{\partial \theta_i} \tag{2.27}$$

where

$$\frac{\partial \log q(y|X,\theta)}{\partial \theta_i}\Big|_{\text{explicit}} = \frac{1}{2}\hat{f}^T K^{-1} \frac{\partial K}{\partial \theta_i} K^{-1} \hat{f} - \frac{1}{2} tr\Big((W^{-1}+K)^{-1}\frac{\partial K}{\partial \theta_i}\Big) \tag{2.28}$$

$$\frac{\partial \log q(y|X,\theta)}{\partial \hat{f}_i} = -\frac{1}{2}\big[(K^{-1}+W)^{-1}\big]_{ii} \frac{\partial^3}{\partial f_i^3} \log p(y|\hat{f}) \tag{2.29}$$

2.3.3 Predictive Probability

Predictive mean can be decided under Laplace's approximation by combining the prediction in regression eq. (2.11) with eq. (2.24)

$$\mathbb{E}[f_*|X,y,x_*] = K(X_*,X)K(X,X)^{-1}\hat{f} = K(X_*,X)\nabla \log p(y|\hat{f}) \tag{2.30}$$

Predictive variance consists of two terms: one from f_* given f, the other from our estimation of f

$$\mathbb{V}[f_*|X,y,x_*] = \mathbb{E}[(f_* - \mathbb{E}[f_*|X,y,x_*])^2] + \mathbb{E}[(\mathbb{E}[f_*|X,x_*,f] - \mathbb{E}[f_*|X,y,x_*])^2] \tag{2.31}$$

using the matrix inversion lemma [15] we get

$$\mathbb{V}[f_*|X,y,x_*] = K(x_*,x_*) - K(x_*,X)(K(X,X)+W^{-1})^{-1}K(X,x_*) \tag{2.32}$$

Predictive probability the new output belong to class 1 is then computed by eq. (2.19) except that the distribution of f_* is now the result of Laplace's approximation with mean and variance as stated above.

$$\bar{\pi}_* \triangleq p(y_* = +1|X,y,x_*) = \int \sigma(f_*)q(f_*|X,y,x_*)df_* \tag{2.33}$$

One may argue that expectation of the prediction could be simply equal to the sigmoidal mean of f_*. These are actually two different things because of the non-linearity of sigmoid function, the first is averaged probability $E[\pi_*|X,y,x_*]$ while the later one is MAP prediction

$\sigma(E[f_*|y])$. Although the final class labels assigned are the same for both cases, only the averaged probability gives the statistically correct results.

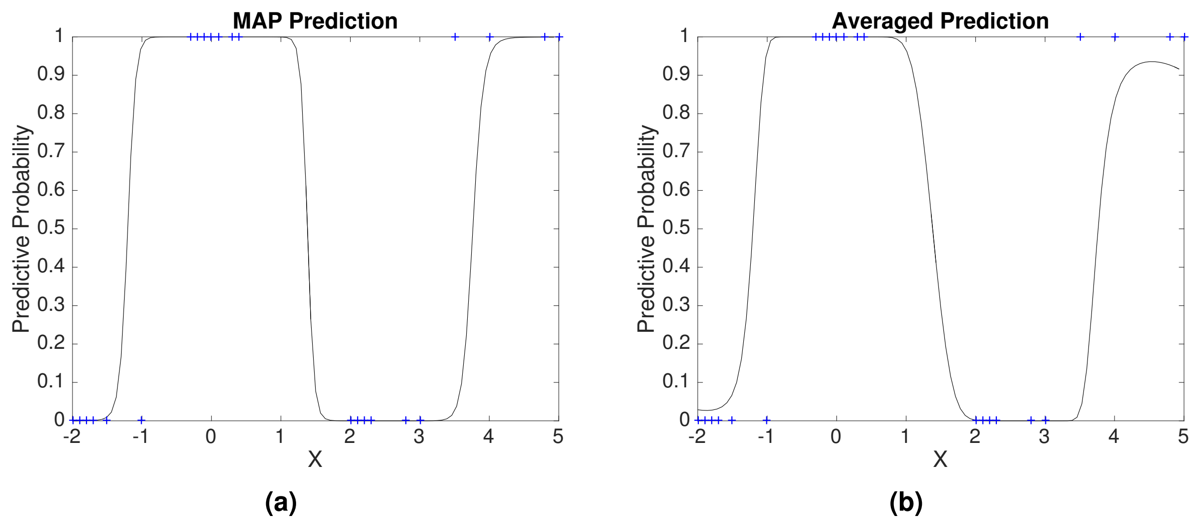


Figure 2.6: (a) the MAP prediction. (b) the averaged probability prediction. Blue crosses are training points (class label 1 and -1 but marked as 1 and 0 for better display). The MAP prediction goes to the extremes quicker while the averaged probability is more moderate and tend to be affected by adjacent points

2.4 Data Preprocessing

Sometimes only the useful information is wanted when data is noisy or redundant. This can be achieved by data preprocessing. It has a few advantages. First, for high dimensional data, computation time is essential. Reducing the redandunt information can largely save computation time. Second, less redundant information means it is easier for your algorithm to find the true pattern behind data.

2.4.1 Principal Component Analysis

Principal Component Analysis (PCA) is a statistical tool for dimensionality reduction. It tries to identify the subspace in which the data approximately lies [16]. It transforms the original data into orthogonal components in descending order of their corresponding variances [17] by eigenvalue decomposition or singular value decomposition [18]. The resulting number of principal components is always equal or less than the original number of dimensions. This can be intuitively explained by the orthogonality of the principal components. Orthogonality means that components are uncorrelated and there are no redundant information between them. Therefore less number of components are needed to represent the data.

The steps for using PCA is very simple: First, normalise the data in each dimension. Next, put it through singular value decomposition. Lastly, cut off all the components with variances less than a threshold. Theshold value depends on how much variances user wants to retained. PCA is widely used in supervised machine learning for faster computation and better knowledge discovery. When dropping the components with less variances, it is equivalently to give up those unimportant features that may had affected the resulting model.

2.4.2 Normalisation

Since PCA is sensitive to the relative scaling of the original variables, normalisation [19] is needed before applying PCA [16]. There are three common methods for normalisation: simple rescaling, per-example mean substraction, and feature standardization. Simple rescaling are usually used in image processing when pixel value is rescaled from [0 255] to [0 1] by dividing 255 on each element. per-example mean substraction is suitable for stationary data that the statistics for each feature dimension is the same. Simply substracting the mean value of each instance will normalise the data. The third one, feature standardization, is the most common method for normalisation. It is achieved by first substract the mean of each dimension from that dimension. Then, each feature dimension is divided by the standard deviation of that dimension. The process makes each dimension to have zero mean and unit variance. With all dimensions having the same scale, PCA can then be applied.

Chapter 3

GP Classification for Employment Prediction

To integrate Gaussian process classification into the prediction of occupational automatability, we first define the occupational features as the input and the probability of computerisation as the output. The basic idea is first to train a classifier based on labeled occupational features. Then the classifier is used to make prediction on occupations with unknown labels, or in other words, to determine the probability of any unknow occupation belonging to class '1'. Here class '1' means the occupation is automatable, and class '0' means it is not automatable. The same class notation will be used through the project.

The optimisation library used

3.1 Performance Measurement

There are two possible measurements for predictive accuracy. One is marginal likelihood calculated in equation 2.26. It is also a measure for choosing hyperparameters. The higher (less

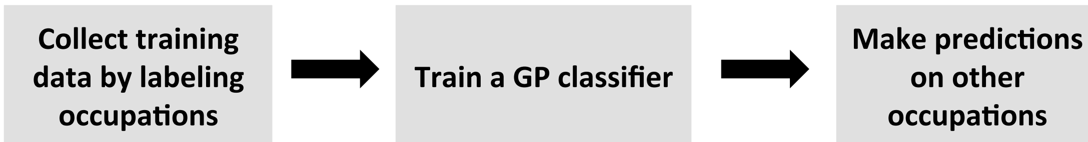


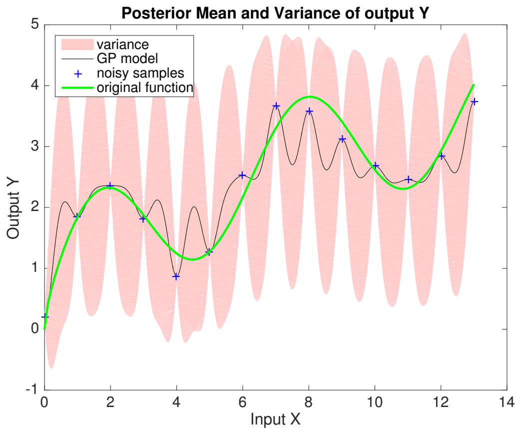
Figure 3.1: A flow chart for how predictions are made

negative) its value is, the better the performance.

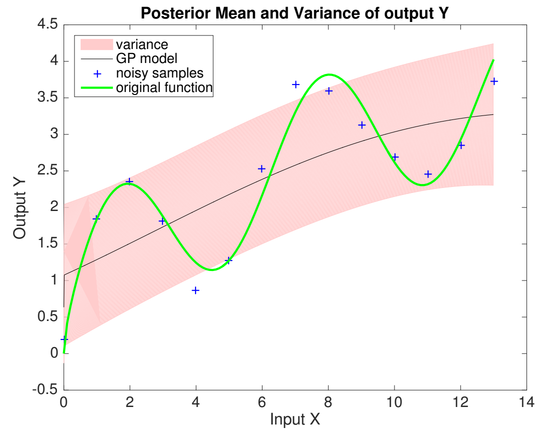
Another important measure commonly used in binary classifier is the Receiver Operating Characteristic (ROC) curve [20] [21]. The curve plots the true positive rate against the false positive rate.The area under the ROC curve (AUC) gives the probability that the classifier gives the right answer for positive classes. A random classifier would score an AUC of 0.5 while a perfect classifier would give the AUC of 1.

There are possibilities of model over-fitting or under-fitting. Whether they would occur depends on the value of hyperparameters. A simple illustration of over-fitting and under-fitting in 1D Gaussian process is shown in Figure 3.2. In the upper left graph, when length scale is small, the model function tries to fit too much details including the unwanted noise. While in the upper right graph, when length scale is too large, the model would only describe a general trend which is not very useful if more information is wanted. The best model is the intermediate state where only the appropriate curvatures are preserved.

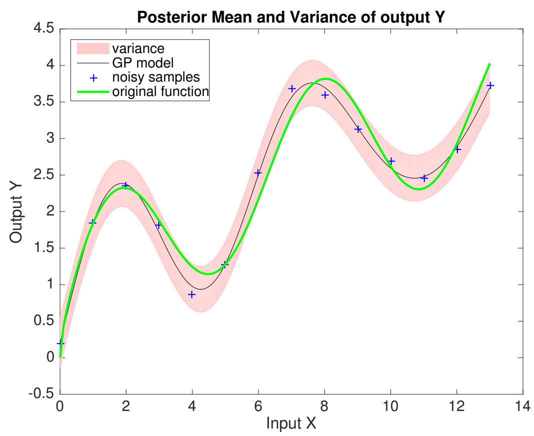
In order to verify that the classifier is working correctly – no over-fitting or under-fitting is happening, AUC is computed by dividing the training data into a testing group and a training group with equal number of members each. The model hyperparameters trained from the training group are used for predicting the testing group labels. Then the result of testing group is compared with its true class labels to generate the ROC curve. A typical ROC curve in this



(a) over-fitting, l = 0.25



(b) under-fitting, l = 12



(c) l = 2

Figure 3.2: (a) When lengthscale get small, it tries to fit the noise-corrupted details (b) If length-scale is contrained to be large, it concenrates on large scale smoothness (c) An appropriate model in this case should pay attention to detail but not forgetting the overall smoothness. Green curve is the original function from which noisy samples (blue corsses) are generated. Black curve is the resulting GP model.

problem would look like figure 3.3. The final model for predicting all occupations are trained on the whole training set which includes the training group and testing group. One thing to notice is that a good algorithm learns the trend from training data while not fitting the noise. Noise can be introduced when the feature variables are noisy or the labels are not 100% correct. An ideal model should be able to identify and correct the mistaken labels therefore would nont neccessary give the lowest training error or the best AUC.

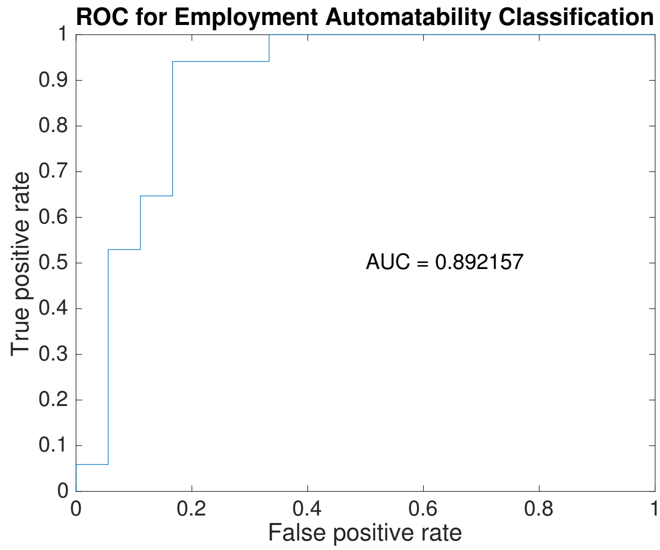


Figure 3.3: A typical ROC curve plotted with 35 training instances.

3.2 The 2010 data

The occupational task descriptions are obtained from the 2010 version of O*NET – an online platform providing detailed descriptions for jobs. Hand-labelled training data with 33 occupations labelled '0'(not automatable) and 37 labelled '1'(fully automatable) are prepared. A job is defined as automatable if all tasks involved in that job can be performed by computer-controlled equipment. More details about how the training data is determined can be found in the work of Frey & Osborne [1].

Nine features, falling into three categories – social intelligence, creative intelligence, and perception and manipulation, are believed to be bottlenecks of computerisation. They are important factors that affect automatability in terms of the intelligence required to perform a job. Hence concatenating these nine features of each occupation into a feature vector would give us the input of the classification algorithm. Using the feature vector and class label for each occupation in the training set, the probability of any other occupation with unseen feature vector can be computed by estimating a latent function and then mapped into a probability value between 0 and 1. Note the probability computed is only suitable for the near future since the labels are based on current techninology capability.

As stated in section 2.2.1, any type of sigmoid function could be used in this mapping. Here cumulative Gaussian function[1]is chosen for its better performance in this particular problem. Squared exponential is chosen as the covariance function as the output is not expected to have any periodicity but a general smoothness would be helpful (occupations with similar feature variables should have a similar probability of being automated). MinConf [22] is used for fast optimisation on multivariate objective function subject to simple constraints on the parameters. The hyperparameters are constrained within a certain range for numerical stability.

The results are shown in Figure 3.4. In stead of plotting original variables against the probability of computerisation, the graphs are generated by plotting the categorical score against probability. The value for each category is calculated by adding up all variables in that category. The categorical plotes shows a clear trend in automatability.

Both creative intellience and social intelligence have a negative effect on probability of computerisation. High values in these variables indicate a lower risk of being automated. On the other hand, occupations with high value in variables of perception and manipulation tend to have a higher risk. For example, 'Mental Health Counselors' needs a high level of social perspectives such as persuation, have a probability as low as 0.048. However, machine operators such as 'Shoe Machine Operators and Tenders' require a relatively higher level of manual dexterity, has a high probability of 0.95. Probability of other occupations can be checked in Appendix A.

It is not hard to tell that occupations involving abstract and creative tasks are not likely to be substituted by machines, at least not now, not on a large scale. Although, it does not mean that

[1] Also know as probit function

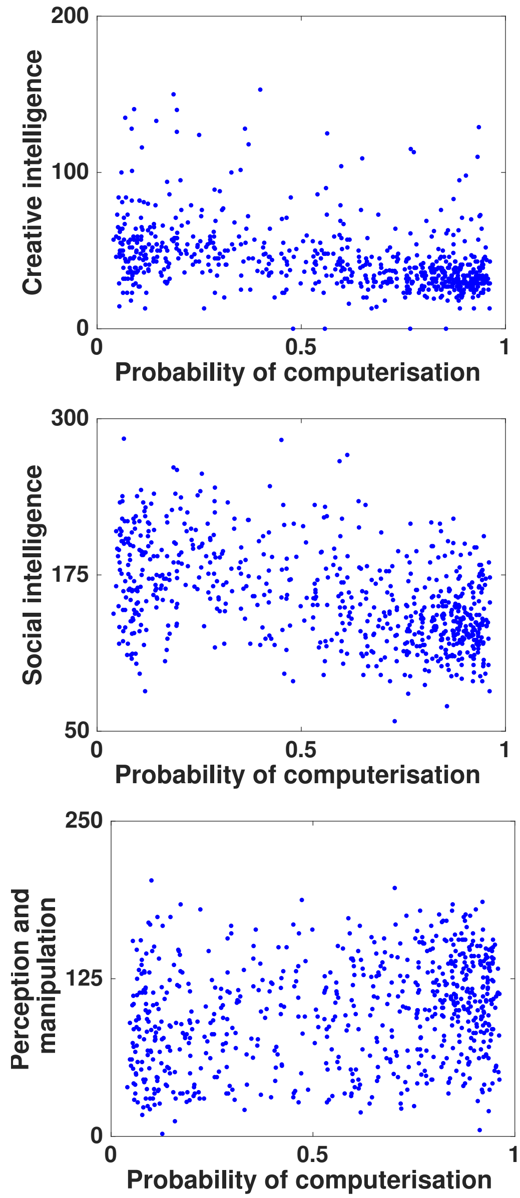


Figure 3.4: The occupational category as a function of probability of computerisation. Each point represents an occupation. The value for each category is compued by adding up all variables within that category but the input for the algorithm is still nine variables.

jobs requiring high creative intelligence and social intelligence will never be automated, it does indicates that these substitution is not happening in the near future given current technology.

However, we should always be aware that these automations could happen when their engineering bottlenecks are broken. At that time, there is no reason for automation not to happen when machines can just perform these tasks as well as human and even at a lower cost. This is exactly what happened after the Great Recession – companies preferred to buy more equipments than hire more employees. It was believed to be the foundamental cause of the slow recovery of labor force market after the recession [5] and it could also be the cause of the next job loss.

3.3 The 1980 data

Occupational data from David Autor et al. [2] includes skills required in each occupation in 1980. In total, there are 26 input variables for each occupation, including different characteristics of the workers such as spatial aptitude, clerical perception, and finger dexterity etc. The variables are chosen from *Handbook for Analyzing Jobs*[2].

First, training labels from the 2010 experiment are transferred to 1980 occupations via crosswalk files [7], [8], and [9], giving 58 labels on the new data. Then the same process as before is applied. In order to get better results on classification and saving computation time, principal component analysis (PCA) is used to reduce the dimensionality of feature vector. 19 components are remained when 98% of variances are preserved. The improvement on performance by using PCA is shown in Table 3.1. Note that data is first normalised before sending into PCA (Section 2.4). This is usually considered as a necessary step for PCA to give a good result [16].

Only five measurements are analysed as representatives for five types of task [2]. They are routine cognitive, routine manual, non-routine analytical, non-routine interactive, and non-routine manual tasks. A task is defined as 'routine' if it can be accomplished by machine

[2]U. S. Department of Labor, Manpower Administration, Handbook for Analyzing Jobs (Washington, DC, 1972)

Performance	no PCA	with PCA
Likelihood	-35.99	-30.65
AUC	0.75	0.87

Table 3.1: Performance with and without PCA

following explicit rules that can be programmed. Many rule-based tasks, such as monitoring the amount of sulphur dioxide in gas emitted by thermal power station, belong to this category. Non-routine tasks are those that can not be programmed in code line by line and therefore are well understood by computers. Another categorization is manual or cognitive. Manual tasks involves physical activities while cognitive tasks involves knowledge works. Cognitive tasks can further be categorised into analytical or interactive, depending on whether it needs mathematical skills or not.

Although the input variables for 2010 and 1980 are both about the level of intelligence required to perform a job, their analysis focus on different perspectives. Previously, the study focused on the relation between score of intelligence and probability. This time, the score of intelligence is used as representatives for different tasks. Certainly there is a correspondence between these two representation. Social intelligence are often required in non-routine interactive tasks while perception and manipulation are mostly performed in either routine or non-routine manual tasks. Similar trends would be expected for corresponding categories. Figure 3.5 are the probability plot for all five tasks. The score of each task is calculated as the percentage of the sum of all five task scores. As expected, high level of non-routine interactive tasks means lower probability of computerisation. High level of routine and non-routine manual tasks gives higher risk for computerisation.

An interesting thing to notice is that the trend for non-routine manual task is more similar

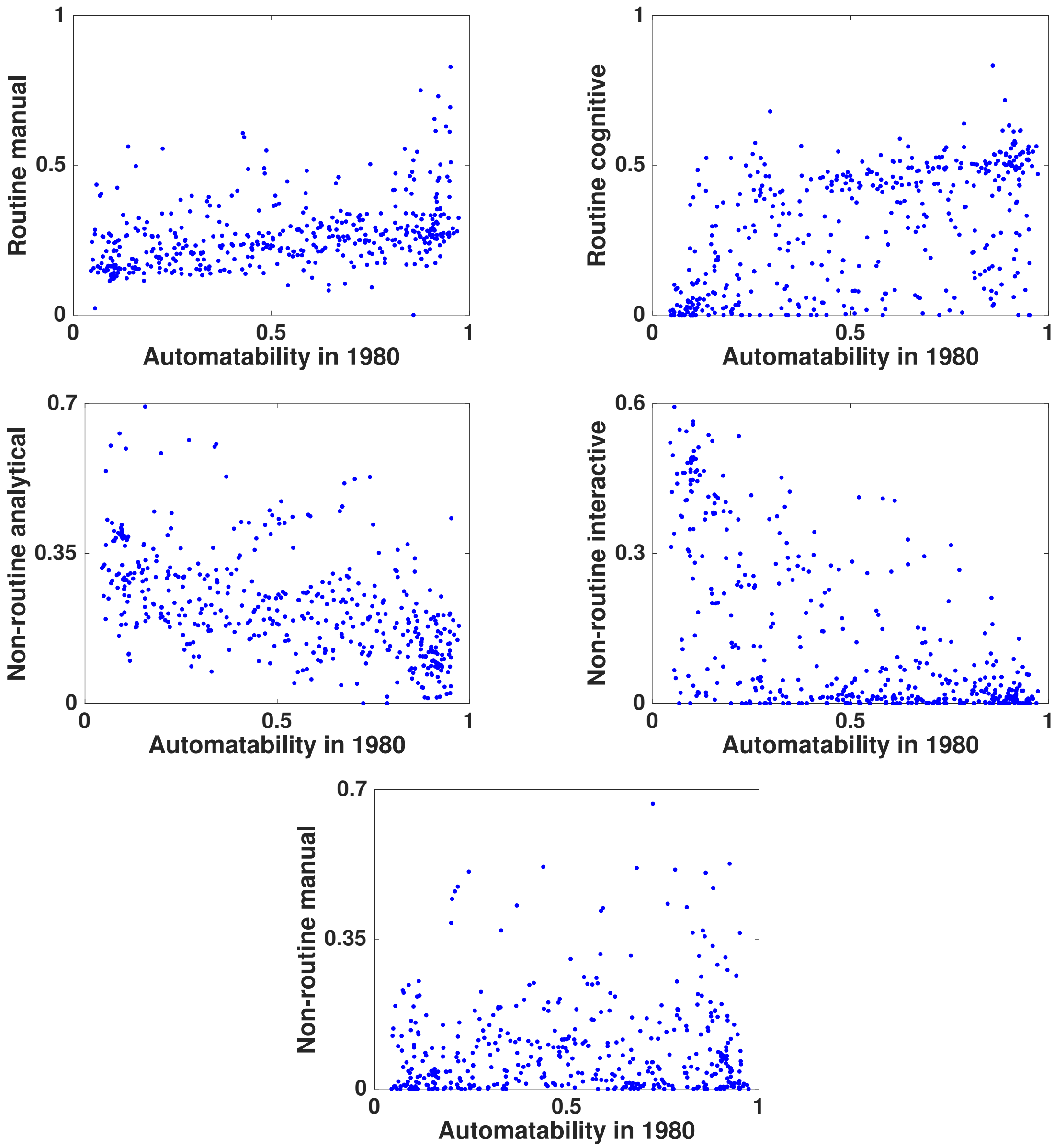


Figure 3.5: The task measurements in 1980 vs. probability of computerisation.

to those of routine tasks. In the 20th century, computerisation is limited within routine tasks that can be performed by following explicit rules. Recent developments in artificial intelligence makes non-routine tasks involving non-rule-based activities such as pattern recognition also become computerisable. This is why non-routine manual task behaves like routine tasks. An example occupation rich in non-routine manual tasks would be drivers. Traditionally, driving a car is treated as a fairly difficult task for machine to complete. Now self-driving car is believed to be undoubtly the next revolution in car industry. Similar things are happening in other areas. All of them contribute to the change of computerisation and as a result shift in job market.

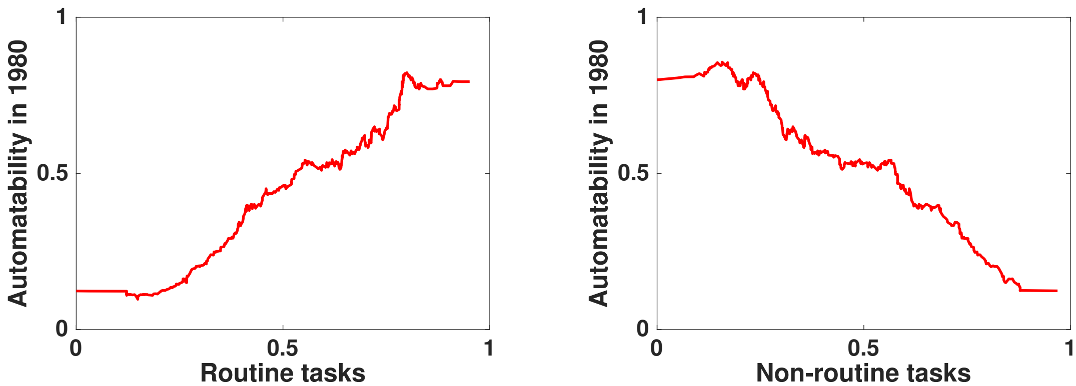


Figure 3.6: Averaged probability of computerisation vs. categorial task measurements in 1980.

Figure 3.6 are the probability for routine tasks and non-routine tasks in general. Again, the categorical task scores are the sum of all variables in each category. The plot is generated by applying a moving average filter over all occuations. There is a steady increase in probability with higher routine tasks and reverse trend in non-routine tasks. The plots matches the conclusion of David Autor et al. [2] that the use of computers is substitutive to routine jobs while complementary to non-routine jobs in general.

To further prove that the result is correct, the employment data from IPUMS [10] is compared with the probability of computerisation in 1980. If the predictions are correct, occupations with high probability of computersation should have decreased in employment rate[3]. If we exclude the extreme values (with more than 0.25 percent change in employment rate) and fit it with a least squre line, we could see a clear trend giving negative relationship between probability and employment change in Figure3.7.

[3]Employment rate here refers to the percentage of population that is working in certain job.

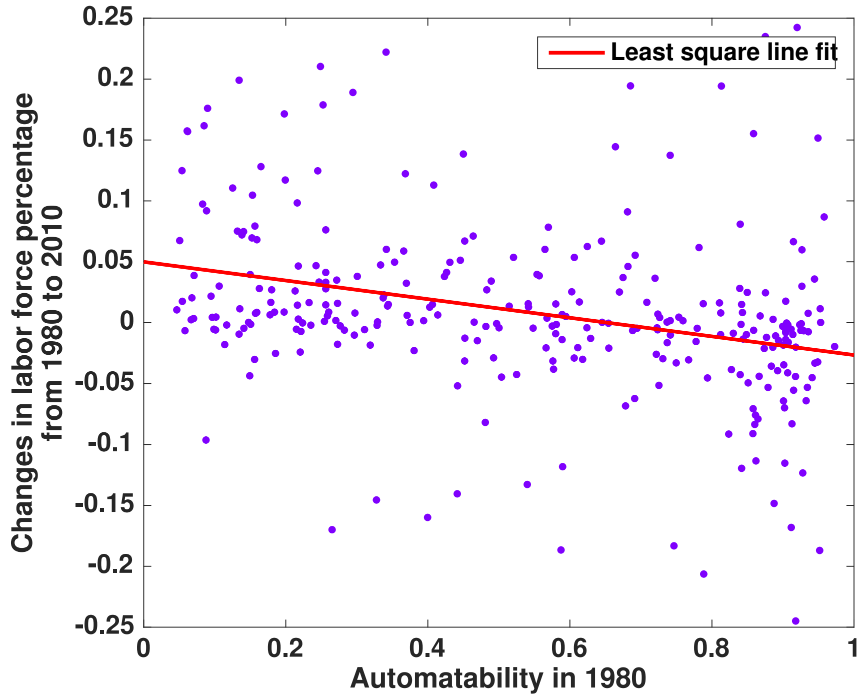


Figure 3.7: Change in employment rate from 1980 to 2010 vs probability of computerisation in 1980. Each point represents an occupation

If we divide the result into low, medium, and high probability range, the average changes in employment rate for each automatability level can be computed in Table 3.2. As expected, high probability of computerisation results in decrease in employment.

On the other hand, the fact that the employment rate of low automatability jobs are more likely to have increased fits well to the opinion of Brynjolfsson and McAfee [5]. They argued

Probability of computerisation	Change in employment rate
low	0.037 ± 0.005
medium	0.002 ± 0.003
high	-0.011 ± 0.006

Table 3.2: Mean and standard deviation of changes in employment rate based on each level of automatability

that computerisation will not make people useless. Instead, it will shift the labor market so that more people are working on those tasks that computers are not good at. As long as human learns to use computers to help them with other non-computerisable tasks, that is to say, to keep computers being complementary instead of substitutive, computers will not be a threat to human jobs. This means two things. First, as computers become cheaper and smarter, more people will use computers as their complementary tool for their jobs today. Second, new jobs will be created by using more powerful computers as infrastructure. The only case we need to worry is when the rate of computer development become faster than the rate at which human creating and adapting to new jobs. If that happens, the employment rate of human race would be expected to decrease.

3.4 Changes in probability from 1980 to 2010

To study how probability of computerisation has changed from 1980 to 2010, the change in probability for each occupation is collected. The histogram is shown in Figure 3.8.

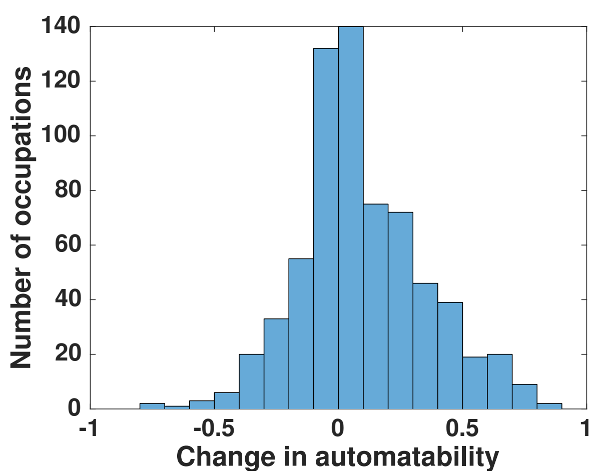


Figure 3.8: Change in probability from 1980 to 2010 histogram.

There are more occupations with increased probability than with decreased probability. It can be explained in two possible ways. First, the same labels are applied to two different data sets. If routine task components in occupations, especially the highly automatable ones, has decreased through the 30 years, an occupation with label ’1’ in 2010 may have lower score in routine tasks than that occupation in 1980. This results in a lower requirement in routine task score for an occupation in 2010 to be classified as ’automatable’. Second, two data sets are using different measuring systems. The 2010 data set takes account of 9 features while the 1980 data have 26 variables. The 1980 data set have measured more features and therefore it may give very different results.

Chapter 4

Conclusion

In this project, the probabilities of future computerisation for occupations in 2010 and 1980 are computed using Gaussian process classification. The result is analysed in two major steps. First, the results are used to find the relation between automatability and the tasks required for each occupation. Second, the results of 1980 occupations are used to predict the employment change which is then examined on the actual history data. In conclusion, jobs with relatively high score in routine tasks, compared to score of non-routine tasks, are more susceptible to computerisation. In contrast, jobs with relatively high demand in non-routine tasks are less likely to be automated.

However, this is just a short term prediction based on current technology. Resistance in automation for non-routine tasks will no longer exits when its related technical bottlenecks are broken. This has already happened in some non-routine tasks. Self-driving cars are emerging these days with the development of artificial intelligence. Robots are learning to write novels. Being affected by these new technologies, the negative relation between non-routine tasks and automatability is no longer hold for non-routine manual tasks. There is no reason for us to not believe that similar things would happen in other areas.

Although the development of technology will make machine more capable of human works, it does not need to become a disaster. The book *The new division of labor: How computers are creating the next job market* [6] believes that what technology do is to shift the the tasks that human workers perform. The investment in computers resulted in striking decrease in routine task frequency while complex communications and expert thinking frequencies increased more than expected. The development of technology is not a threaten to human workers as a whole. Although it does decline the labor force of occupations that involves routine tasks that computers can perform, at the same time, it pushed more people to take more complex tasks that computers cannot do.

4.1 Limitations

There are potential errors in the employment prediction. First, the crosswalk files did not make perfect matches for occupation from 1980 and 2010 because of change of occupational structures. Some 2010 occupations can not find correspondencies in 1980 simply because they did not exist at that time. Some may find multiple correspondences because jobs branch and merge over time. Therefore it may be better if more precise labels could be determined individually other than relying on crosswalks to tranfer from the 2010 labels. In addition, the mismatch of occupations causes a small amount of data loss when comparing probabilities, which may or may not have affected the final results.

Other factors such as politics may also affect the actual automatability. This project only discusses the computerisation from a technical point of view – which occupations are at a risk to be automated given current technology. Also, it is not taking into account the possible future developments in new technology. The breaking of engineering bottlenecks in the future, obviously, will again change the image of computerisation probability.

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Appendix A

Probabilities of computerisation

Occupation		Probability of computerisation		Change in employment rate
Name	label	2010	1980	
Recreational Therapists		0.036	0.256	0.04100
Emergency Management Directors		0.041	0.141	0.07500
Psychologists All Other		0.042	0.106	0.03000
First-Line Supervisors of Mechanics Installers and Repairers		0.046	0.301	0.03800
Social and Community Service Managers	0	0.047	0.129	
Healthcare Social Workers		0.048	0.051	0.06700
Mental Health Counselors		0.048	0.198	0.17100
Occupational Therapists		0.049	0.256	0.02800
Audiologists		0.051	0.256	0.03300
Physicians and Surgeons	0	0.051		
Instructional Coordinators		0.052	0.103	0.70800
Dentists General	0	0.053	0.070	0.00300
First-Line Supervisors of Fire Fighting and Prevention Workers		0.053	0.216	0.01400
Elementary School Teachers Except Special Education		0.054	0.075	0.29500
Speech-Language Pathologists		0.054	0.256	0.03300
Clergy	0	0.066	0.157	0.07900
Educational Guidance School and Vocational Counselors		0.067	0.198	0.17100
Career/Technical Education Teachers Secondary School		0.068	0.088	-0.09600
Preschool Teachers Except Special Education	0	0.071	0.054	0.12500

Occupation		Probability of computerisation		Change in employment rate
Name	Label	2010	1980	
Secondary School Teachers Except Special and Career/Technical Education		0.071	0.088	-0.09600
Sales Managers		0.081	0.068	0.02000
Public Relations and Fundraising Managers		0.084	0.068	0.02000
Logisticians		0.085	0.426	0.04100
Pharmacists		0.086	0.163	0.02800
Registered Nurses	0	0.086		
First-Line Supervisors of Production and Operating Workers		0.097	0.196	-0.60900
Rehabilitation Counselors		0.098	0.198	0.17100
Chief Executives	0	0.098	0.158	0.40700
Materials Engineers		0.099	0.254	0.00100
Education Administrators Preschool and Childcare Center/Program	0	0.099	0.085	0.16200
Materials Scientists		0.099	0.319	-0.01800
Fashion Designers	0	0.100	0.165	0.12800
First-Line Supervisors of Office and Administrative Support Workers		0.100	0.450	0.13800
Civil Engineers	0	0.102	0.233	0.01600
Photographers		0.102	0.135	0.01100
Marriage and Family Therapists	0	0.115	0.198	0.17100
Interior Designers		0.116	0.165	0.12800
Writers and Authors		0.120	0.342	0.06000
Meeting Convention and Event Planners	0	0.123	0.129	
Chiropractors		0.133	0.179	0.01700
Multimedia Artists and Animators		0.133	0.157	0.00800
Lawyers	0	0.139	0.090	0.17600
Landscape Architects	0	0.142	0.054	0.01800
Social Scientists and Related Workers All Other		0.149	0.406	0.01500
First-Line Supervisors of Correctional Officers		0.150	0.245	0.12500
Commercial and Industrial Designers		0.152	0.165	0.12800
Broadcast News Analysts		0.162	0.184	0.00900
Occupational Therapy Assistants		0.163	0.256	0.02800
Substance Abuse and Behavioral Disorder Counselors	0	0.174	0.198	0.17100
Fine Artists Including Painters Sculptors and Illustrators		0.182	0.157	0.00800
Graphic Designers		0.185	0.165	0.12800
Chefs and Head Cooks	0	0.196	0.252	0.17900
First-Line Supervisors of Non-Retail Sales Workers		0.201	0.112	0.76200
Radio and Television Announcers	0	0.206	0.235	-0.00200
Electrical Engineers		0.210	0.149	-0.04400
Compliance Officers	0	0.214	0.515	0.01400
Dancers		0.246	0.329	0.00100

Occupation		Probability of computerisation		Change in employment rate
Name	Label	2010	1980	
Childcare Workers	0	0.247	0.400	
Licensed Practical and Licensed Vocational Nurses		0.249	0.095	0.02200
Healthcare Practitioners and Technical Workers All Other	0	0.251		
Petroleum Engineers		0.252	0.394	0.00200
Animal Trainers		0.253	0.788	-0.20600
Physicists	0	0.266	0.215	-0.00500
Hairdressers Hairstylists and Cosmetologists	0	0.266	0.138	0.07200
Computer Hardware Engineers		0.292	0.149	-0.04400
Agents and Business Managers of Artists Performers and Athletes		0.292	0.097	0.00400
Career/Technical Education Teachers Middle School		0.327	0.075	0.29500
First-Line Supervisors of Retail Sales Workers		0.329	0.112	0.76200
Geographers		0.333	0.406	0.01500
Financial Analysts		0.340	0.295	0.18900
Concierges	0	0.352	0.580	0.01500
Athletes and Sports Competitors	0	0.371	0.088	0.09200
Zoologists and Wildlife Biologists	0	0.377	0.159	0.00800
Firefighters		0.390	0.216	0.01400
Financial Specialists All Other		0.397	0.295	0.18900
Private Detectives and Investigators		0.415	0.199	0.11700
Architectural and Civil Drafters		0.453	0.858	-0.09100
Economists	0	0.456	0.446	0.05100
Judges Magistrate Judges and Magistrates	0	0.459	0.054	
Surveyors	1	0.461	0.217	
Computer Programmers		0.477	0.645	0.32900
Advertising Sales Agents		0.483	0.180	0.02700
Ambulance Drivers and Attendants Except Emergency Medical Technicians		0.483	0.782	0.06200
Judicial Law Clerks	1	0.484	0.685	0.19400
Merchandise Displayers and Window Trimmers		0.508	0.165	0.12800
Plumbers Pipefitters and Steamfitters	0	0.510	0.504	-0.04500
Costume Attendants		0.517	0.565	0.06000
Agricultural Engineers		0.522	0.243	0.04700
Aerospace Engineering and Operations Technicians		0.539	0.681	0.09100
Radiation Therapists		0.540	0.256	0.04100
Machinists		0.559	0.590	-0.11800
Life Physical and Social Science Technicians All Other		0.560	0.681	0.09100
Transportation Storage and Distribution Managers	0	0.560	0.726	0.00400

Occupation		Probability of computerisation		Change in employment rate
Name	Label	2010	1980	
Market Research Analysts and Marketing Specialists	1	0.568	0.141	0.07500
Cost Estimators	1	0.574	0.129	
First-Line Supervisors of Farming Fishing and Forestry Workers		0.578	0.812	-0.01000
Social Science Research Assistants		0.580	0.681	0.09100
Personal Financial Advisors		0.596	0.295	0.18900
Commercial Pilots		0.605	0.403	0.01300
Flight Attendants	0	0.612	0.370	0.03200
Fire Inspectors and Investigators		0.615	0.216	0.01400
Police Fire and Ambulance Dispatchers		0.627	0.521	0.05400
Mine Shuttle Car Operators		0.627	0.903	-0.11500
Massage Therapists		0.628	0.408	0.11300
Purchasing Agents Except Wholesale Retail and Farm Products		0.646	0.218	0.04700
Correctional Officers and Jailers		0.658	0.245	0.12500
Court Municipal and License Clerks		0.661	0.843	0.00800
Dental Assistants		0.668	0.198	0.00900
Avionics Technicians		0.670	0.500	-0.00400
Civil Engineering Technicians	1	0.678	0.681	0.09100
Bartenders		0.681	0.750	-0.03300
Crossing Guards		0.692	0.594	0.00500
Electronic Equipment Installers and Repairers Motor Vehicles		0.693	0.500	-0.00400
Recreational Vehicle Service Technicians		0.698	0.541	0.01600
Motorboat Operators	1	0.700	0.589	-0.01400
Electrical and Electronics Drafters	1	0.707	0.858	-0.09100
Computer Automated Teller and Office Machine Repairers		0.727	0.464	0.07100
Barbers		0.728	0.273	-0.01800
Hunters and Trappers	0	0.740		
Dental Hygienists		0.753	0.247	0.03300
Motorcycle Mechanics		0.755	0.741	0.00200
Cutters and Trimmers Hand		0.758	0.913	-0.08300
Welding Soldering and Brazing Machine Setters Operators and Tenders		0.761	0.888	-0.14800
Carpenters		0.761	0.328	-0.14600
Technical Writers	1	0.778	0.218	0.00300
Computer-Controlled Machine Tool Operators Metal and Plastic	1	0.782	0.603	0.02500
Foundry Mold and Coremakers		0.789	0.901	-0.06400
Motorboat Mechanics and Service Technicians		0.791	0.741	0.00200
Bus Drivers Transit and Intercity	1	0.803	0.682	0.04600
Postal Service Mail Carriers		0.807	0.953	0.00000
Power Plant Operators		0.810	0.371	0.00600
Sheet Metal Workers	1	0.815	0.557	0.03900

Occupation		Probability of computerisation		Change in employment rate
Name	Label	2010	1980	
Light Truck or Delivery Services Drivers	1	0.821	0.861	-0.07600
Maids and Housekeeping Cleaners	0	0.822	0.368	0.12200
Laundry and Dry-Cleaning Workers		0.828	0.901	-0.03500
Personal Care Aides		0.829	0.111	0.44400
Insurance Sales Agents		0.843	0.858	-0.07100
Dishwashers	1	0.848	0.850	0.02500
Accountants and Auditors	1	0.848	0.686	0.32600
Chemical Plant and System Operators		0.853	0.849	-0.01000
Human Resources Assistants Except Payroll and Timekeeping	1	0.862	0.907	-0.01600
Tax Examiners and Collectors and Revenue Agents	1	0.866	0.686	0.32600
Patternmakers Metal and Plastic		0.868	0.778	-0.01500
Parking Lot Attendants	1	0.869	0.724	0.00700
Railroad Brake Signal and Switch Operators		0.869	0.827	-0.03900
Cooks Fast Food	1	0.870	0.252	0.17900
Meter Readers Utilities	1	0.872	0.859	-0.00600
Taxi Drivers and Chauffeurs	1	0.872	0.782	0.06200
Compensation and Benefits Managers		0.878	0.152	0.07000
Maintenance Workers Machinery		0.878	0.877	-0.01200
Forest and Conservation Workers		0.880	0.812	-0.01000
Nonfarm Animal Caretakers		0.882	0.720	0.03600
Paralegals and Legal Assistants	1	0.886	0.685	0.19400
Parking Enforcement Workers		0.890	0.245	0.12500
Bus Drivers School or Special Client		0.901	0.682	0.04600
Medical Transcriptionists	1	0.907	0.664	0.14400
Sewing Machine Operators	1	0.907	0.708	-0.45400
Real Estate Brokers		0.913	0.337	0.02000
Credit Analysts	1	0.914	0.295	0.18900
Butchers and Meat Cutters		0.915	0.725	-0.05100
Helpers–Carpenters		0.915	0.875	0.02500
Food and Tobacco Roasting Baking and Drying Machine Operators and Tenders		0.915	0.375	0.00000
Electrical and Electronic Equipment Assemblers	1	0.916	0.927	-0.52900
Bicycle Repairers		0.917	0.541	0.01600
Gaming Dealers	1	0.919	0.565	0.06000
Couriers and Messengers	1	0.921	0.915	0.06700
File Clerks	1	0.923	0.911	-0.00500
Cement Masons and Concrete Finishers		0.927	0.741	-0.01000
Refuse and Recyclable Material Collectors		0.928	0.924	-0.00200
Claims Adjusters Examiners and Investigators	1	0.929	0.741	0.13700
Industrial Truck and Tractor Operators	1	0.930	0.861	-0.07600
Waiters and Waitresses	0	0.934	0.587	-0.18700
Mail Clerks and Mail Machine Operators Except Postal Service		0.935	0.934	-0.05300

Occupation		Probability of computerisation		Change in employment rate
Name	Label	2010	1980	
Payroll and Timekeeping Clerks		0.935	0.973	-0.02000
Radio Operators		0.938	0.688	-0.00600
Farm Labor Contractors	1	0.939	0.812	-0.01000
Woodworking Machine Setters Operators and Tenders Except Sawing		0.939	0.935	0.00800
Legal Secretaries		0.942	0.294	-0.56700
Postal Service Clerks		0.943	0.860	-0.08400
Switchboard Operators Including Answering Service	1	0.945	0.912	-0.16800
Shoe Machine Operators and Tenders		0.945	0.866	-0.04400
Driver/Sales Workers		0.946	0.861	-0.07600
Telephone Operators		0.946	0.912	-0.16800
Data Entry Keyers	1	0.948	0.945	-0.03300
Shipping Receiving and Traffic Clerks		0.951	0.862	-0.11300
Insurance Underwriters	1	0.951	0.839	0.02800
Pesticide Handlers Sprayers and Applicators Vegetation		0.952	0.626	0.27600
Cashiers	1	0.954	0.776	0.31900
Credit Authorizers Checkers and Clerks	1	0.956	0.692	0.05500
Loan Officers	1	0.957	0.295	0.18900
Library Technicians		0.961	0.482	-0.00300
Tax Preparers		0.962	0.295	0.18900
Telemarketers		0.962	0.663	-1.65100

Table A.1: Probability of computerisation in 1980 and 2010 (some 1980 reaults are missing because they can not find correspondences using crosswalk files).