

# 資料分析

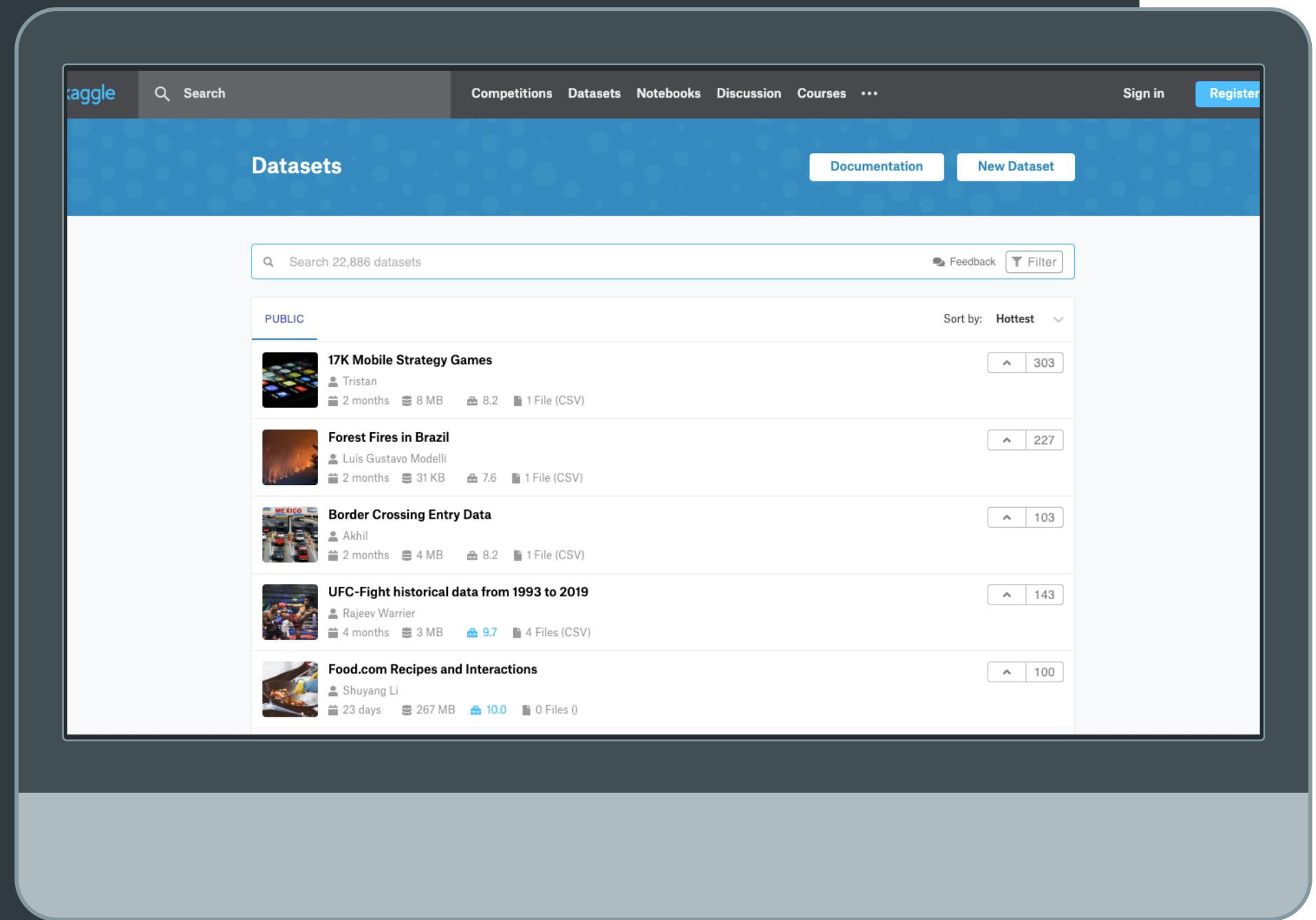
## Gender Recognition by Voice

組員：

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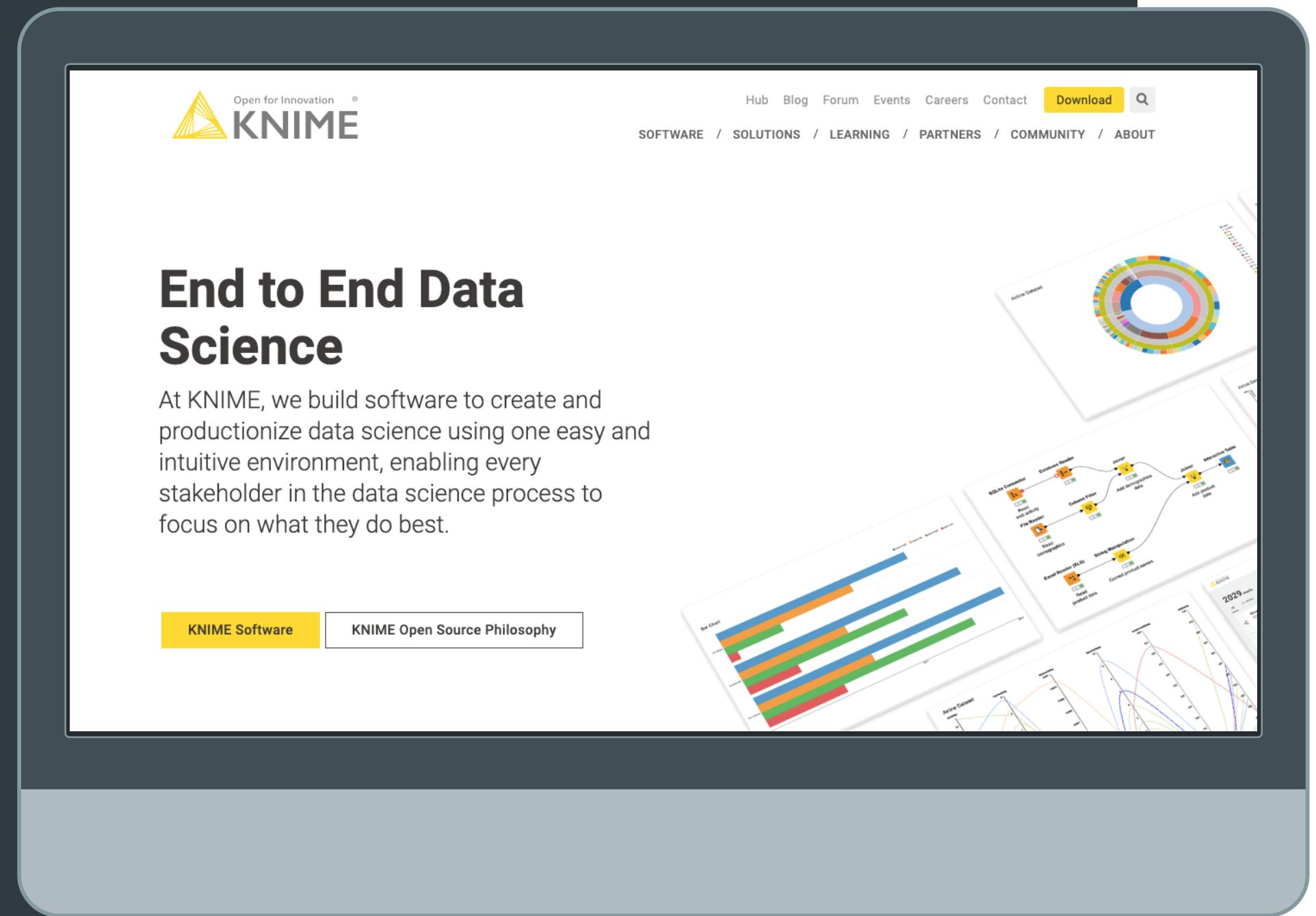
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# Use the dataset By Kaggle

<https://www.kaggle.com/primaryobjects/voicegender>



# Analyze the dataset By KNIME

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<https://www.knime.com/>

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## SECTION 1

What's your data mining problem?

# Gender Recognition by Voice and Speech Analysis

## Identify a voice as male or female

- This database was created to identify a voice as male or female, based upon **acoustic properties** of the voice and speech.
- The dataset consists of **3,168** recorded voice samples, collected from male and female speakers.
- The voice samples are pre-processed by acoustic analysis in R using the seewave and tuneR packages, with an analyzed frequency range of 0hz-280hz

# Question

## ■ 主要

1. 男性和女性聲音之間還有哪些其他特徵？
2. 可以發現男性和女性聲音在共鳴(resonance)上有區別嗎？

## ■ 次要

1. 可以從正常聲音中識別假音(falsetto)嗎？（為此可能需要單獨的數據集）
2. 數據中還有其他有趣的功能嗎？

“以人耳看來，用聲音決定性別能否依靠簡單的頻率來決策呢？”



SECTION 2

# Data understanding

# Dataset

data categories

- Dataset: 3618\*21
- Filename: voice.csv
- Data based on acoustic properties of the voice and speech (frequency:kHz)
  - meanfreq、sd、median、Q25、Q75、IQR、skew、kurt、sp.ent、sfm、mode、centroid、meanfun、minfun、maxfun、meandom、mindom、maxdom、dfrange、modindx、class

# Data Attribute-acoustic properties

//頻率以kHz為單位

- meanfreq:平均頻率
- sd:頻率標準差
- median:中位數頻率
- Q25、Q75:第1、3四分位數
- IQR:四分位距(Q75-Q25)
- skew:偏斜
- kurt:峰度
- sp.ent:頻譜熵
- sfm:頻譜平坦度
- mode: 頻率眾數

- centroid:頻率重心
- meanfun:跨聲學信號測得的**基本頻率**的平均值
- minfun:跨聲學信號測得的最小基頻
- maxfun:跨聲學信號測得的最大基頻
- meandom:整個聲信號測得的主頻的平均值
- mindom:跨聲學信號測得的最小主頻
- maxdom:跨聲信號測得的主頻率最大值
- dfrange:跨聲信號測得的主頻範圍
- modindx:調製指數。計算為相鄰基頻測量之間的累計絕對差除以頻率範圍
- class:男性或女性

# Meandom(average dominant frequency)

- 口語中的頻率變化很大，更不用說整個句子了。頻率隨著語調而上升和下降，通常是在單詞和語音中傳達某些情感。這可能使查明準確的頻率變得困難。
- 可以通過使用每個語音樣本中測得的平均主導頻率。
- 關於性別，平均主導頻率的確具有統計學意義。因為皆是正值，因此這支持了基本假設，即頻率的增加與女性的語音分類相對應。

# Fundamental frequency(基本頻率)

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- males ranges from 100 to 150 Hz
- females ranges from 180 to 250 Hz

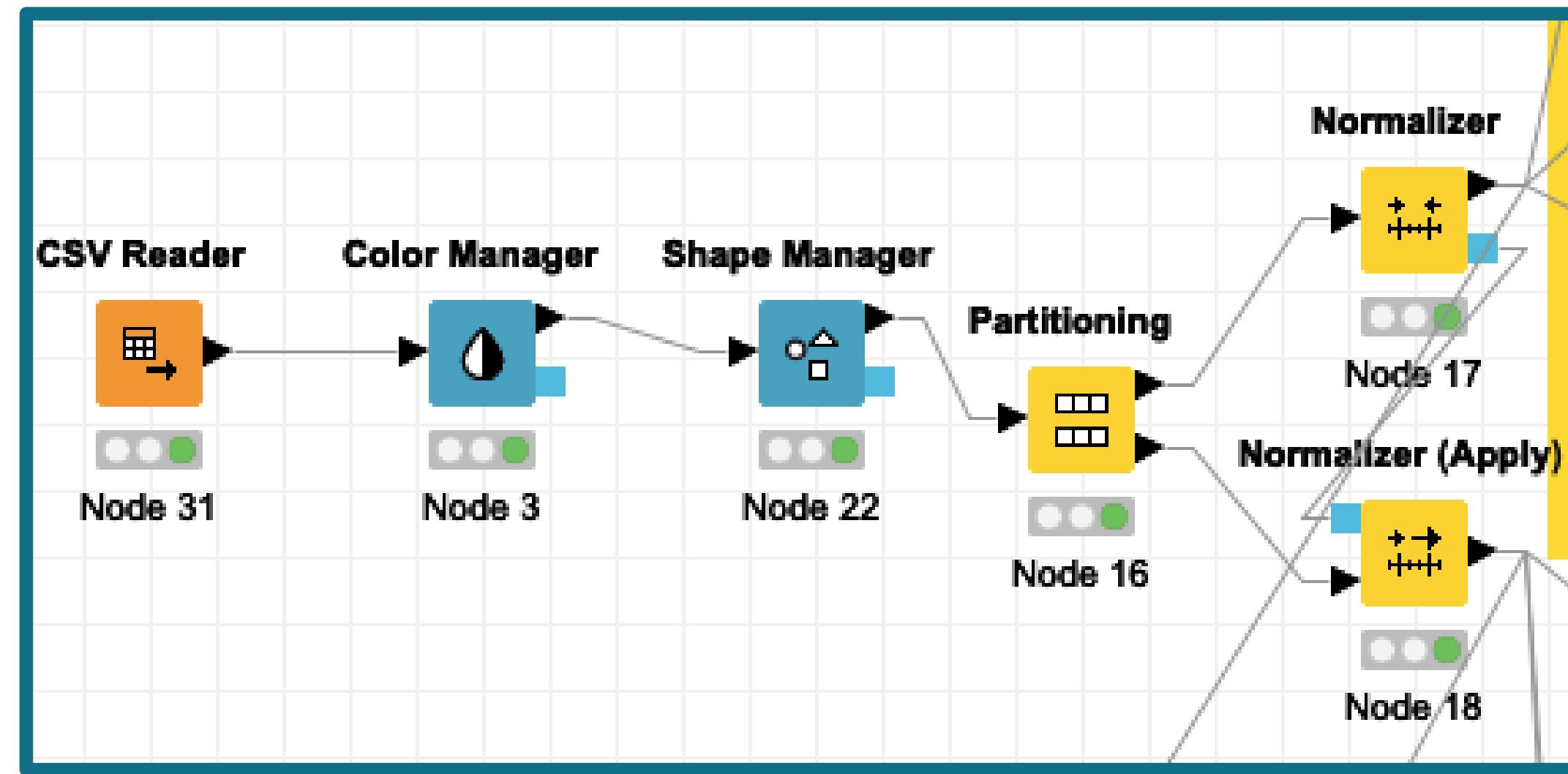
SECTION 3

# Data preparation

# Analysis

## Use different algorithm

- 找到適合的演算法，達到精準的分析
- 用不同的演算法進行分析，例如
  - a. Logistic Regression
  - b. Random forest
  - c. SVM
- 對dataset進行feature selection以及降維(using PCA)



# Data preparation

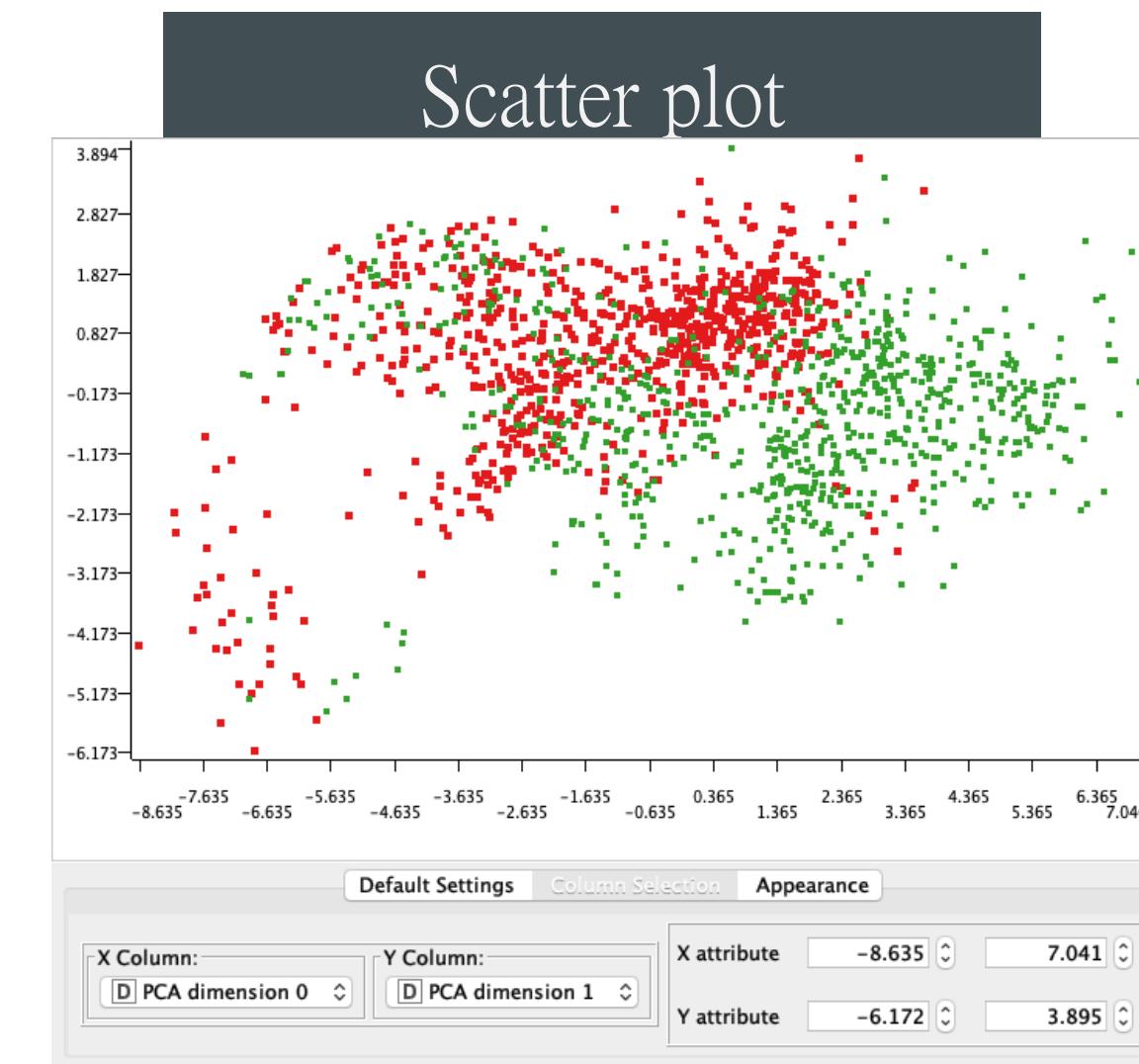
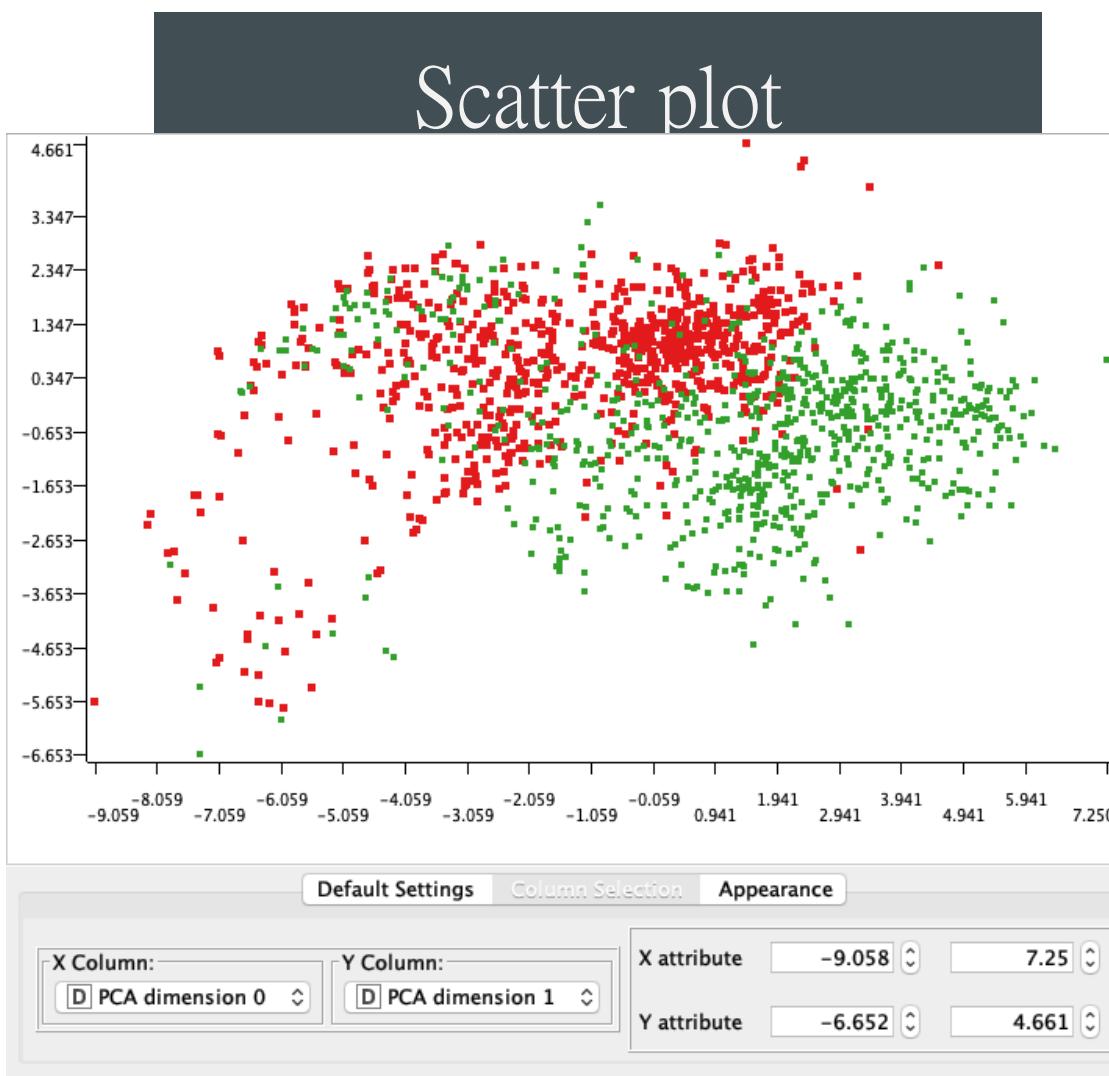
Import 資料庫檔案(voice.csv) → 進行 color/shape manager  
 → partitioning(relative 50%) → Normallizer(using z-score)



SECTION 4

# Result and Discussion

# PCA Dimension Reduction to 2dim.



- PCA training

X:PCA0

Y:PCA1

- PCA testing

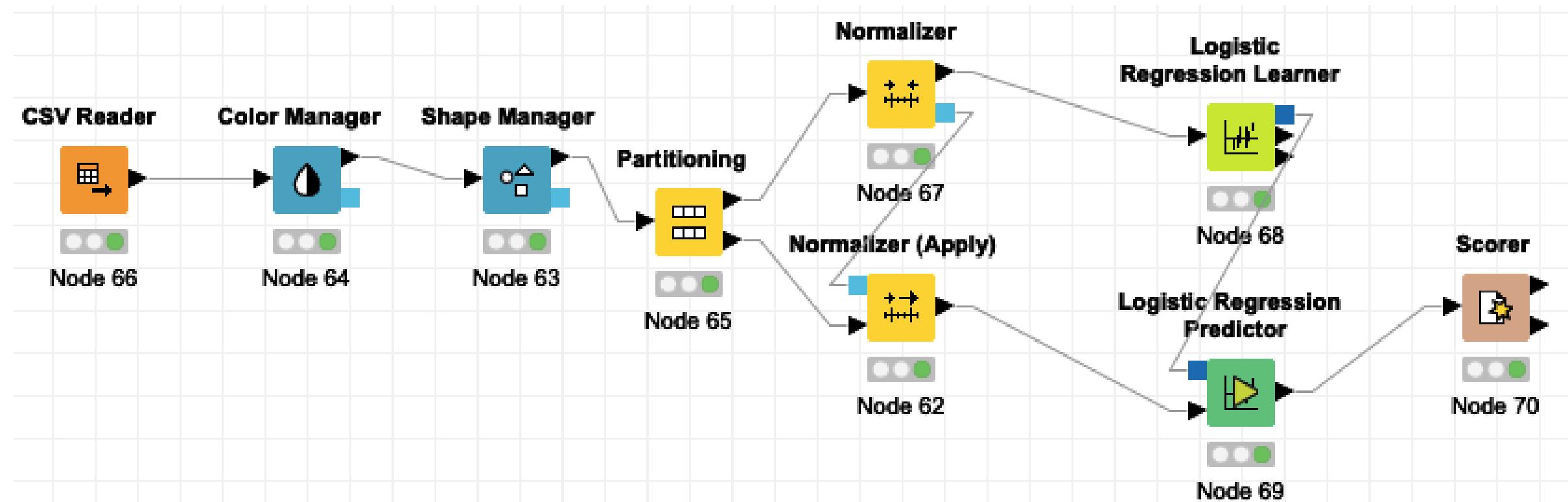
X:PCA0

Y:PCA1

# Use Only meandom

- 另外，我們對於單一頻率，只使用meandom，用邏輯回歸模型透過訓練，在測試上的準確性為56.313%。準確度達到一半左右，但仍遠不能準確檢測男性/女性聲音。

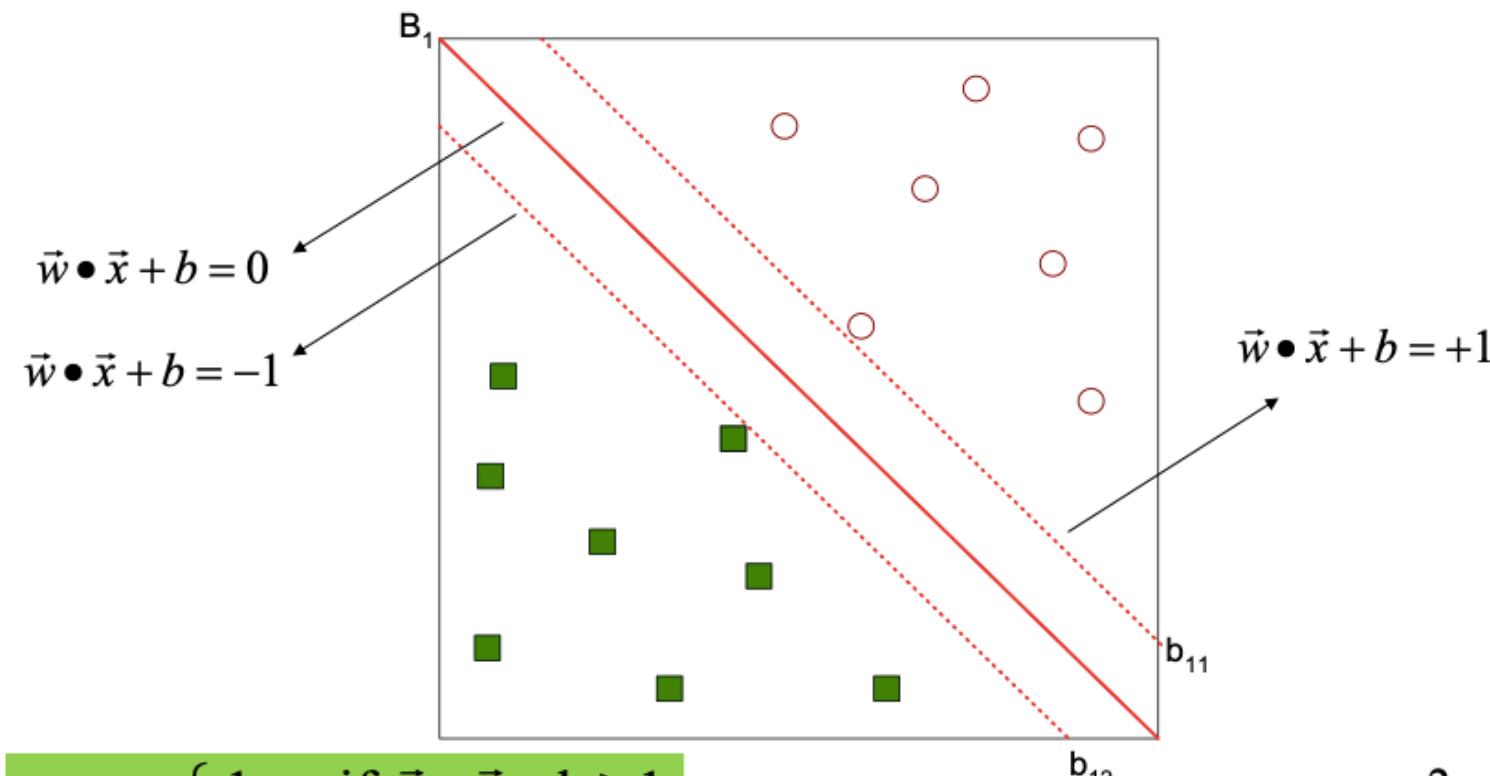
Correct classified: 892	Wrong classified: 692
Accuracy: 56.313 %	Error: 43.687 %
Cohen's kappa ( $\kappa$ ) 0.126	



# SVM

- SVM是一種監督式的學習(Supervised learning)方法，其概念非常簡單，就是找到一個決策邊界(decision boundary)讓兩類之間的邊界(margins)最大化，使其可以完美區隔開來。

## Support Vector Machines

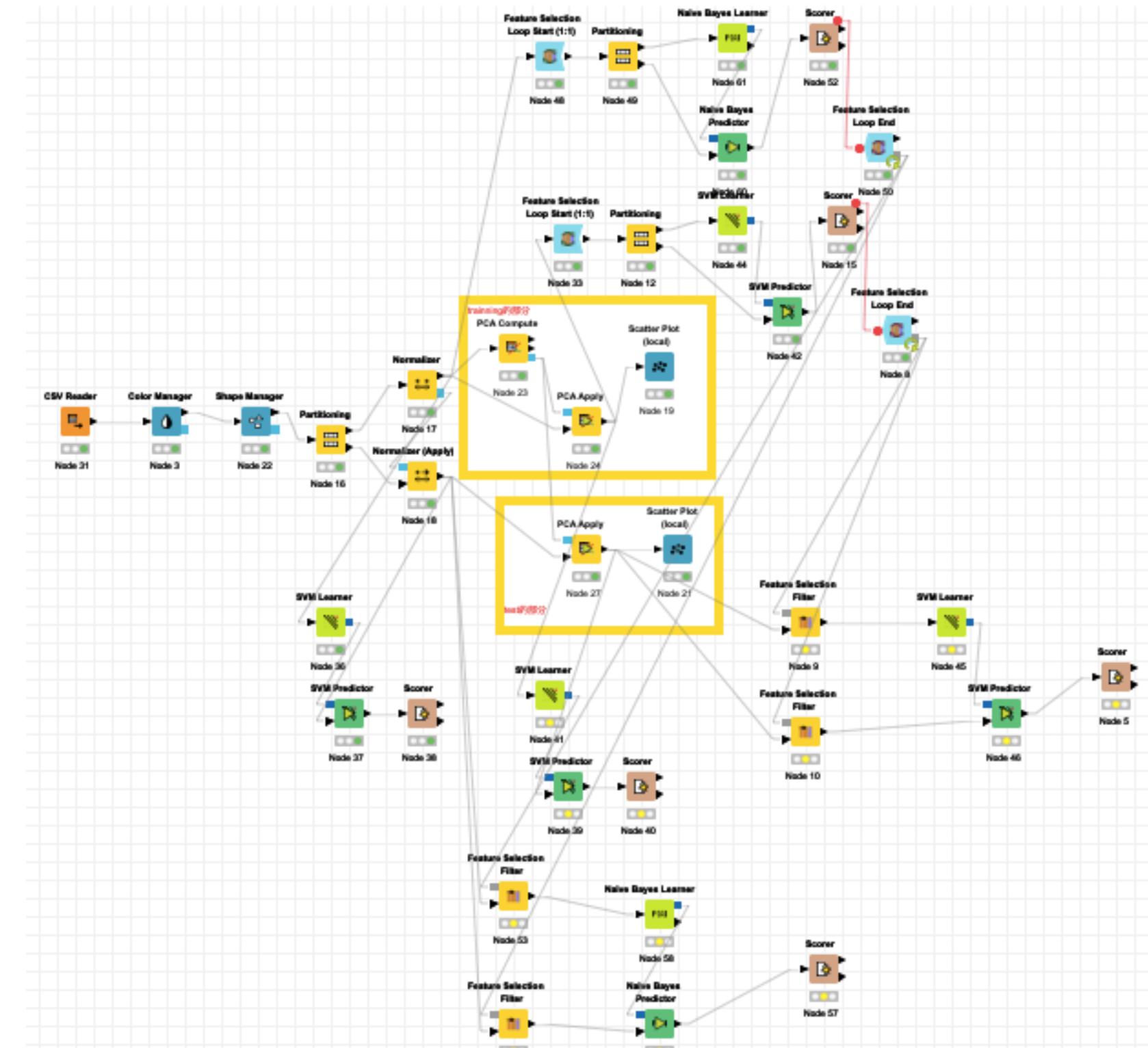


$$f(\vec{x}) = \begin{cases} 1 & \text{if } \vec{w} \cdot \vec{x} + b \geq 1 \\ -1 & \text{if } \vec{w} \cdot \vec{x} + b \leq -1 \end{cases}$$

$$\text{Margin} = \frac{2}{\|\vec{w}\|}$$

PCA	Feature selection	Accuracy(%) by SVM
✗	✗	97.475
✗	✓	97.727
✓	✗	97.475
✓	✓	97.033

# SVM workflows



# Feature selection for SVM

## Feature selection

Dialog - 0:53 - Feature Selection Filter

Include static columns  
 Select features manually  
 Select features automatically by score threshold  
Prediction score threshold

Accuracy	Nr. of features	
0.986	17	D meanfreq
0.981	15	D sd
0.98	18	D median
0.98	16	D Q25
0.98	11	D Q75
0.98	9	D IQR
0.979	14	D skew
0.977	6	D kurt
0.976	10	D sp.ent
0.976	7	D sfm
0.975	8	D mode
0.975	4	D centroid
0.973	13	D meanfun
0.972	5	D minfun
0.971	12	D maxfun
0.971	20	D meandom
0.97	19	D mindom
0.968	3	D maxdom
0.967	2	D dfrange
0.963	2	D modindx
0.948	1	S class

OK Apply Cancel ?

Dialog - 0:9 - Feature Selection Filter

Include static columns  
 Select features manually  
 Select features automatically by score threshold  
Prediction score threshold

Accuracy	Nr. of features	
0.981	6	D meanfreq
0.98	6	D sd
0.98	9	D median
0.98	8	D Q25
0.979	19	D Q75
0.979	14	D IQR
0.979	12	D skew
0.979	11	D kurt
0.977	5	D sp.ent
0.975	18	D sfm
0.975	10	D mode
0.975	7	D centroid
0.973	16	D meanfun
0.973	4	D minfun
0.972	17	D maxfun
0.972	15	D meandom
0.972	13	D mindom
0.971	20	D maxdom
0.971	3	D dfrange
0.971	2	D modindx
0.968	22	S class
0.968	21	D PCA dimension 0
0.952	1	D PCA dimension 1

OK Apply Cancel ?

# SVM Confusion matrix

None and PCA

class \ Pre...	male	female
male	768	24
female	16	776

Correct classified: 1,544  
Accuracy: 97.475 %  
Cohen's kappa ( $\kappa$ ) 0.949

Wrong classified: 40  
Error: 2.525 %

Feature selection

class \ Pre...	male	female
male	773	19
female	17	775

Correct classified: 1,548  
Accuracy: 97.727 %  
Cohen's kappa ( $\kappa$ ) 0.955

Feature selection + PCA

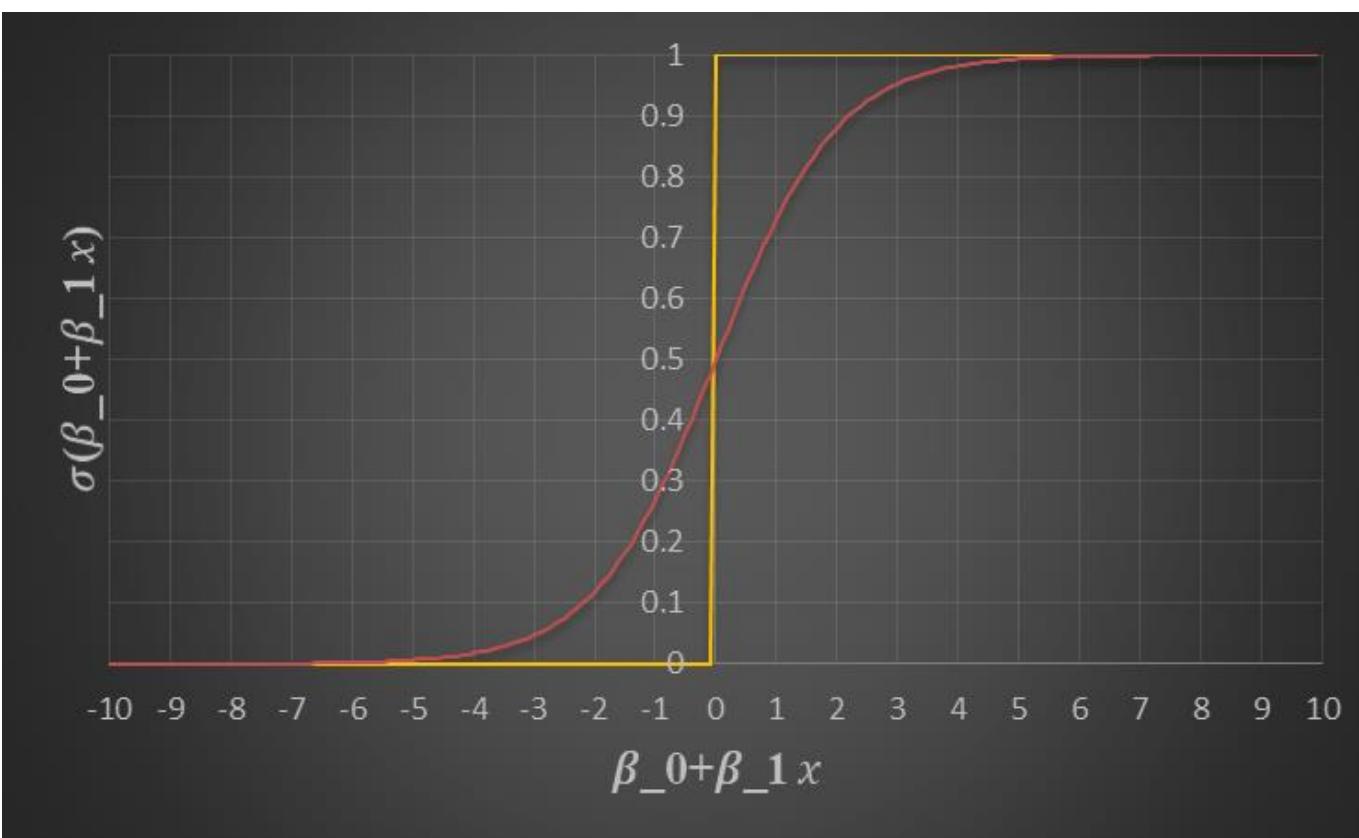
class \ Pre...	male	female
male	769	23
female	24	768

Correct classified: 1,537  
Accuracy: 97.033 %  
Cohen's kappa ( $\kappa$ ) 0.941

Wrong classified: 47  
Error: 2.967 %

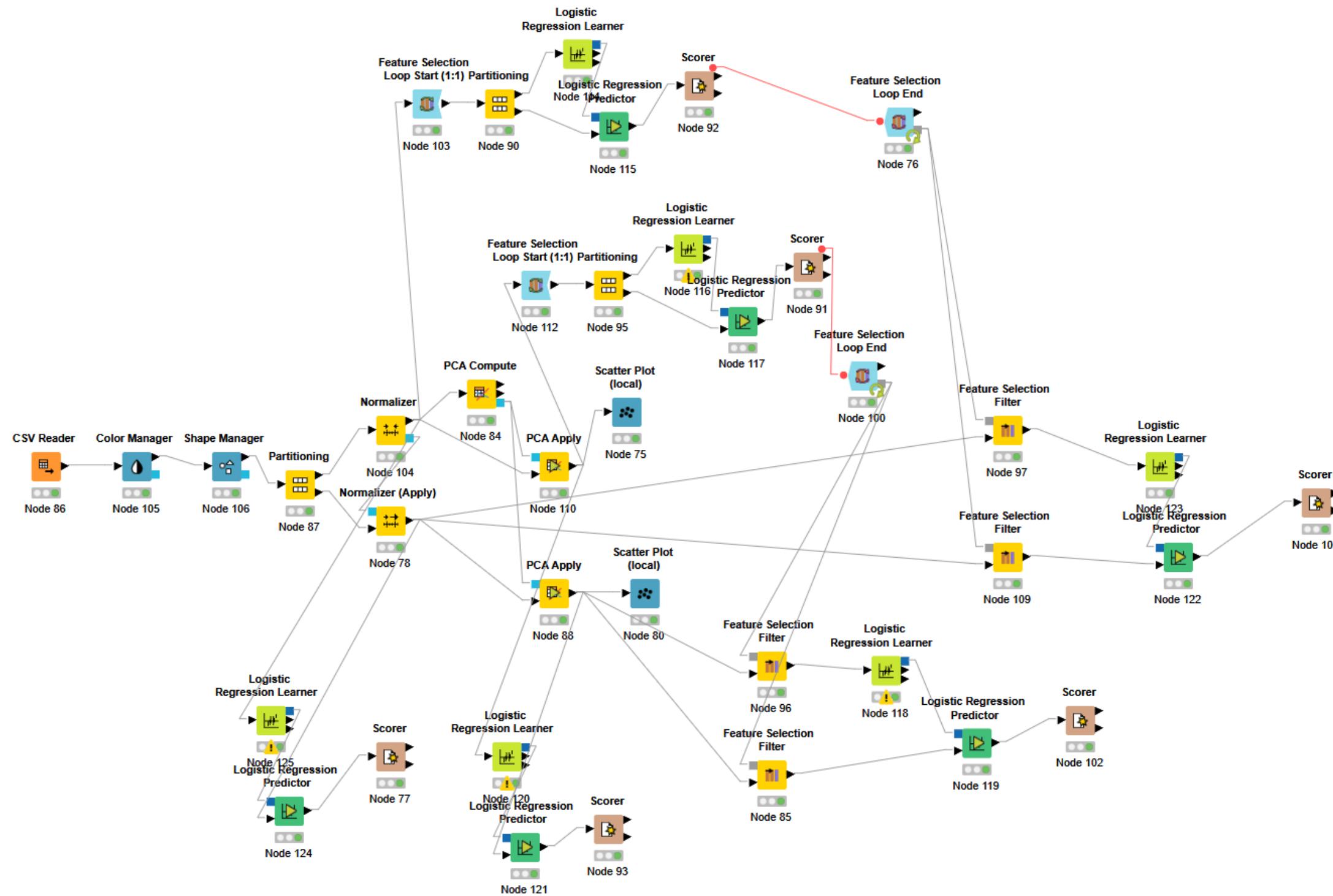
# Logistic Regression

- 一種統計模型，其基本形式是使用logistic函數對二進制因變量進行建模，儘管存在許多更複雜的擴展。在回歸分析中，邏輯回歸是在評估邏輯模型的參數



PCA	Feature selection	Accuracy(%) by Logistic Regression
✗	✗	96.465
✗	✓	96.402
✓	✗	96.843
✓	✓	97.412

# Logistic Regression workflows



# Feature selection for Logistic Regression

## Feature selection

Dialog - 0:97 - Feature Selection Filter

File

Column Selection Flow Variables Memory Policy

Include static columns  
 Select features manually  
 Select features automatically by score threshold  
Prediction score threshold

Accuracy	Nr. of features
0.982	12
0.98	15
0.98	5
0.979	9
0.979	8
0.979	7
0.977	20
0.977	20
0.977	17
0.976	18
0.976	10
0.976	6
0.976	4
0.975	11
0.975	3
0.972	14
0.972	13
0.968	16
0.966	16
0.96	19
0.96	2
0.953	1

meanfreq  
sd  
median  
Q25  
Q75  
IQR  
skew  
kurt  
sp.ent  
stm  
mode  
centroid  
meanfun  
minfun  
maxfun  
meandom  
mindom  
maxdom  
dfrange  
modindx  
class

OK Apply Cancel ?

Dialog - 0:97 - Feature Selection Filter

File

Column Selection Flow Variables Memory Policy

Include static columns  
 Select features manually  
 Select features automatically by score threshold  
Prediction score threshold

Accuracy	Nr. of features
0.982	12
0.98	15
0.98	5
0.979	9
0.979	8
0.979	7
0.977	20
0.977	17
0.976	18
0.976	10
0.976	6
0.976	4
0.975	11
0.975	3
0.972	14
0.972	13
0.968	16
0.966	16
0.96	19
0.96	2
0.953	1

meanfreq  
sd  
median  
Q25  
Q75  
IQR  
skew  
kurt  
sp.ent  
stfm  
mode  
centroid  
meanfun  
minfun  
maxfun  
meandom  
mindom  
maxdom  
dfrange  
modindx  
class

OK Apply Cancel ?

# Logistic Regression Confusion matrix

None

PCA

Feature selection

Feature selection + PCA

class \ Predi...	male	female
male	773	19
female	37	755

Correct classified: 1,528  
Accuracy: 96.465 %  
Cohen's kappa (K) 0.929

class \ Predi...	male	female
male	774	18
female	39	753

Correct classified: 1,527  
Accuracy: 96.402 %  
Cohen's kappa (K) 0.928

class \ Predi...	male	female
male	773	19
female	31	761

Correct classified: 1,534  
Accuracy: 96.843 %  
Cohen's kappa (K) 0.937

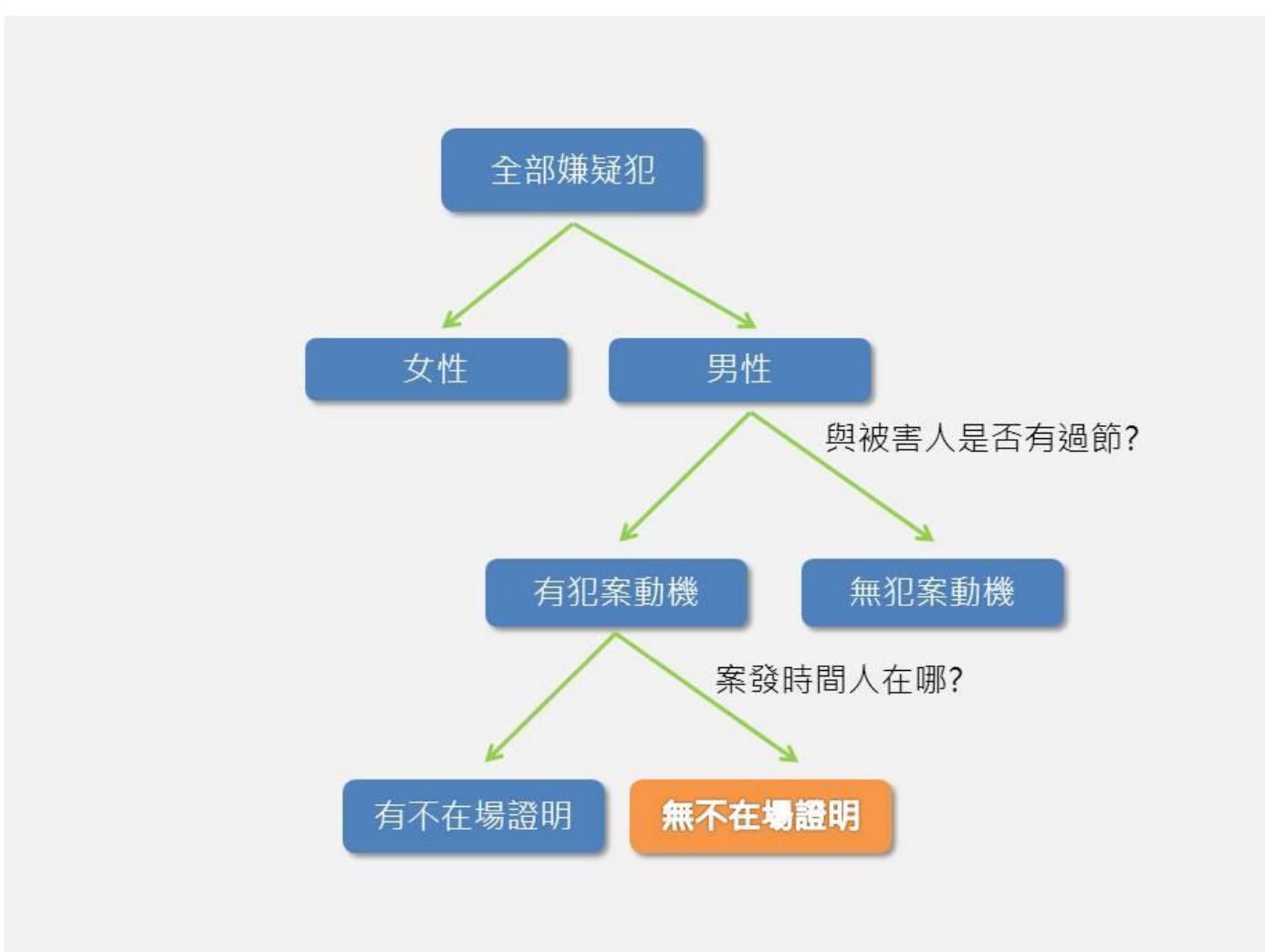
class \ Predi...	male	female
male	775	17
female	24	768

Correct classified: 1,543  
Accuracy: 97.412 %  
Cohen's kappa (K) 0.948

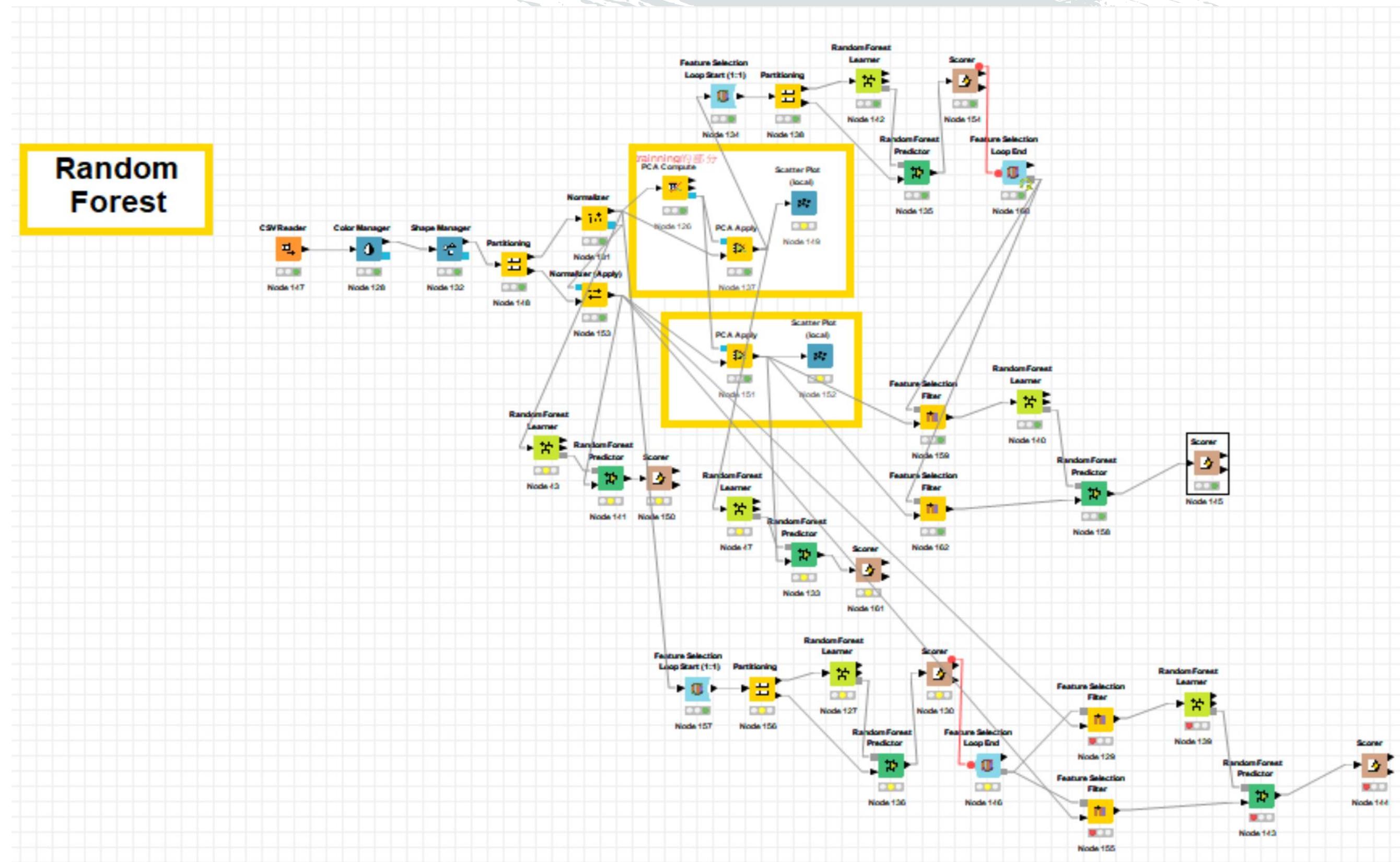
# Random Forest

- 隨機森林其實就是進階版的決策樹，這句話簡單說明，就是很多顆樹加起來可以變成一座森林。



PCA	Feature selection	Accuracy(%) by Random Forest
✗	✗	97.917
✗	✓	97.917
✓	✗	100
✓	✓	100

# Random Forest workflows



# Feature selection for Random Forest

## Feature selection

Column Selection		
	Flow Variables	Memory Policy
<input checked="" type="checkbox"/> Include static columns		
<input checked="" type="radio"/> Select features manually		
<input type="radio"/> Select features automatically by score threshold		
Prediction score threshold	0	<input type="button" value="▲"/>
Accuracy	Nr. of features	
0.986	14	D meanfreq
0.985	21	D sd
0.985	20	D median
0.985	16	D Q25
0.985	16	D Q75
0.985	15	D IQR
0.985	15	D skew
0.985	10	D kurt
0.985	3	D sp.ent
0.984	13	D sfm
0.984	12	D mode
0.984	9	D centroid
0.984	4	D meanfun
0.982	18	D minfun
0.981	11	D maxfun
0.981	7	D meandom
0.981	6	D mindom
0.981	5	D maxdom
0.98	19	D dfrange
0.979	17	D modindx
0.979	8	S class
0.977	22	D PCA dimension 0
0.968	2	D PCA dimension 1
0.929	1	

## Feature selection + PCA

Column Selection		
	Flow Variables	Memory Policy
<input checked="" type="checkbox"/> Include static columns		
<input checked="" type="radio"/> Select features manually		
<input type="radio"/> Select features automatically by score threshold		
Prediction score threshold	0	<input type="button" value="▲"/>
Accuracy	Nr. of features	
0.985	16	D meanfreq
0.984	17	D sd
0.982	6	D median
0.981	14	D Q25
0.981	13	D Q75
0.981	13	D IQR
0.981	12	D skew
0.981	8	D kurt
0.981	8	D sp.ent
0.98	11	D sfm
0.98	9	D mode
0.98	7	D centroid
0.98	4	D meanfun
0.979	19	D minfun
0.979	18	D maxfun
0.979	5	D meandom
0.977	20	D mindom
0.977	15	D maxdom
0.977	10	D dfrange
0.975	3	D modindx
0.963	2	S class
0.931	1	

# Random Forest Confusion matrix

None

PCA

Feature selection

Feature selection + PCA

Confusion Matrix - 3:150 - Scorer			Confusion Matrix - 3:161 - Scorer			Confusion Matrix - 3:145 - Scorer			Confusion Matrix - 3:145 - Scorer		
File Hilite		File Hilite		File Hilite		File Hilite		File Hilite		File Hilite	
class \ Predi...	male	female	class \ Predi...	male	female	class \ Predi...	male	female	class \ Predi...	male	female
male	773	19	male	774	18	male	792	0	male	792	0
female	14	778	female	15	777	female	0	792	female	0	792
Correct classified: 1,551		Wrong classified: 33		Correct classified: 1,551		Wrong classified: 33		Correct classified: 1,584		Wrong classified: 0	
Accuracy: 97.917 %		Error: 2.083 %		Accuracy: 97.917 %		Error: 2.083 %		Accuracy: 100 %		Error: 0 %	
Cohen's kappa (K) 0.958		Cohen's kappa (K) 0.958		Cohen's kappa (K) 1		Cohen's kappa (K) 1		Cohen's kappa (K) 1		Cohen's kappa (K) 1	

# Result and Discussion

- 不管是透過PCA,feature selection，其準確度相差不遠
- 不管是透過SVM,random forest,logistic regression，其準確度相差不遠，若使用random forest精準度可以高達100%
- 對於男性如果發出較高頻率的聲音(假音)，有可能造成誤判
- Partitioning多少與結果並無影響，我們有嘗試過使用不同的partitioning，重新execute了10多次，進行分析後與relative 50%的準確度相差不遠
- 本次使用的dataset僅僅是世界77億人口中的一小部分，如果可以加大資料集，那訓練結果也會更好，但也只是接近100%，仍還是需要其他的features來準確辨別性別

# SECTION 5 Reflection



# Reflection

[https://github.com/king87515/knime\\_voice\\_project](https://github.com/king87515/knime_voice_project)

- 透過這次project，對於KNIME的操作更熟悉
  - Ex: CSV reader,PCA,color/shape manager,plot,feature selection,etc.
- Kaggle裡面的資料集很多，也有很多問題在討論區得到解答，裡面的reference也很用幫助
- 對一些machine learning的演算法更加了解，以及如何使用與操作
- 原本對於一些統計方面的東西不夠了解，藉由這次機會了解了更多
- 一直對於資料處理、分析這塊很有興趣，是一門學問很大、很淵博、實用的工具
- 了解到一些聲學性質與名詞

# References

- <https://www.kaggle.com/primaryobjects/voicegender>
- <http://www.primaryobjects.com/2016/06/22/identifying-the-gender-of-a-voice-using-machine-learning/>
- <https://github.com/primaryobjects/voice-gender>
- <http://notebookpage1005.blogspot.com/2018/03/random-forest.html>

THANK YOU!