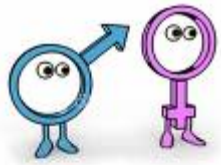

Gender Classification based on Facial information

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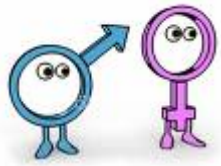
16TH SUMMER SCHOOL ON IMAGE PROCESSING
JULY 7TH-16TH 2008, VIENNA, AUSTRIA.

JULY 15, 2008.

The project team

Layout



- Problem statement.
- State of the Art.
- The system overview.
  - Principal Component Analysis.
  - Fisher Linear Discriminator.
  - Common Vector method.
  - Support Vector Machines.
- Simulations & Results.
- Conclusion.
- Future Perspectives.

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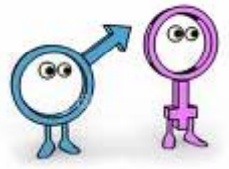
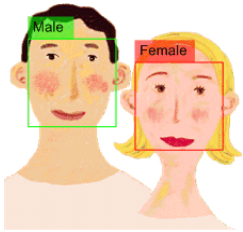
- **Men and Women: Same Species, Different Planets**





- Mathematical/Image processing viewpoint:
  - Binary classification:
    - provided limited prior information.
    - An elevated difficulty level for local probability distribution modeling of the test data.

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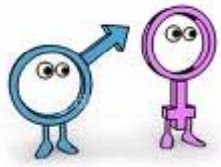

- Local features
  - Skin colour, shape & size of the face, amount of hairs, shape & colour of the lips...
  - Higher difficulty level.
  - Classification accuracies are mediocre.

- Global features
  - Whole facial signature considered as a complete feature set.
  - Useful training sequences required.
  - Higher classification accuracies.
  - Subspace methods + Statistical Learners:
    - Principal Component Analysis (*PCA*).
    - Fisher Linear Discriminator (*FLD*).
    - Common Vectors (*CV*).
    - Support Vector Machines (*SVM*).

    .....

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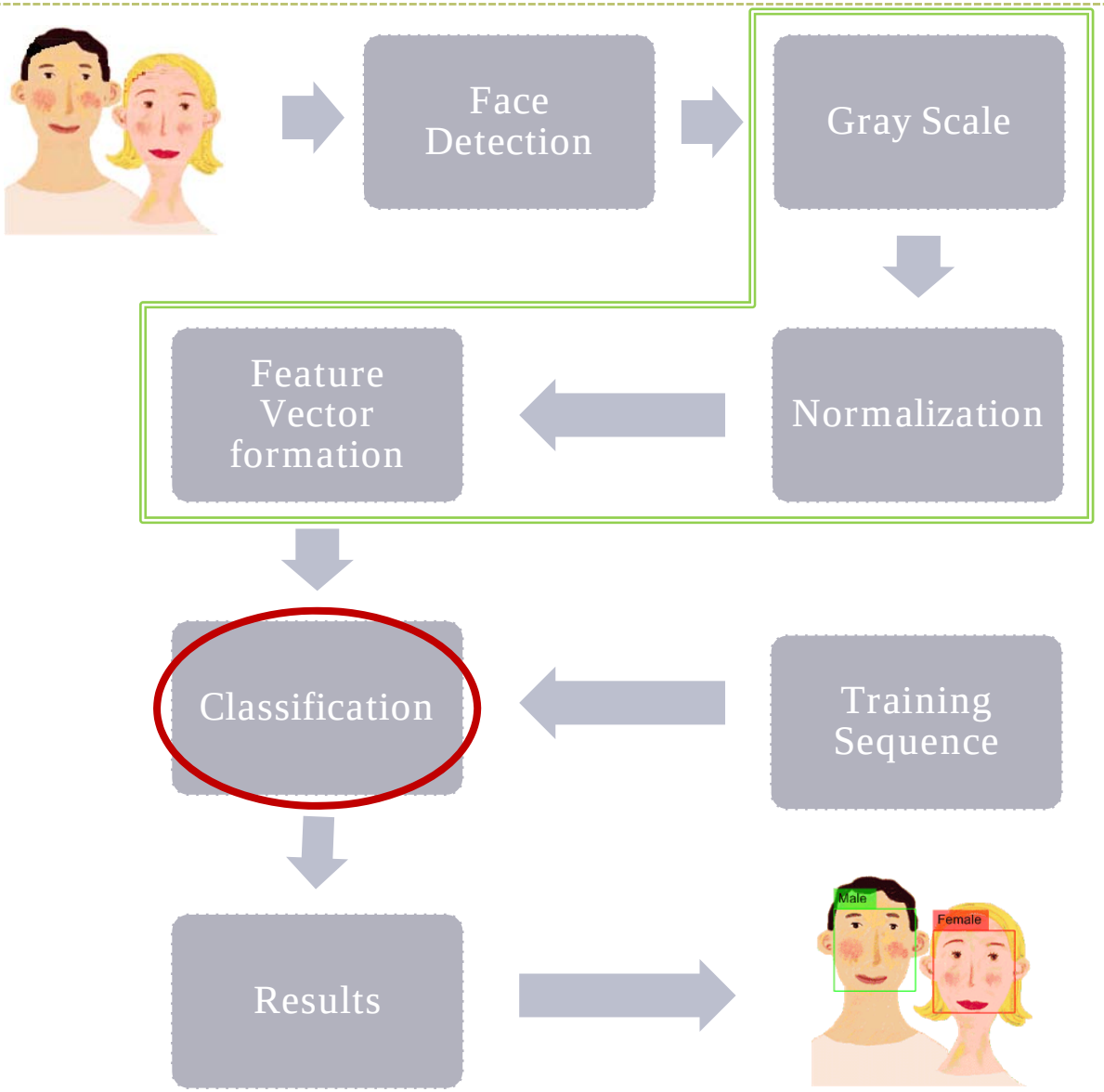
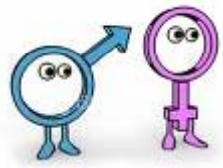




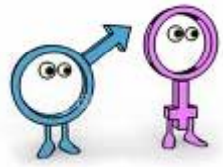
- Karhunen-Loeve Transform (*KLT*).
- Maps vectors from an *M-d* space to a *n-d* space ; *n* << *M*.
- Computes eigenvectors of the *covariance* matrices for normal distributions.

$$\boldsymbol{C} = \frac{1}{r}\sum_{j=1}^{r} \boldsymbol{d}_j \boldsymbol{d}_j^{\mathrm{T}} \quad , \quad \boldsymbol{Z} = (z_1, z_2, \ldots, z_n)^{\mathrm{T}}$$

$$\varepsilon_i = \|\boldsymbol{Z}_{\mathrm{new}} - \boldsymbol{Z}_i\|$$

$$s = \arg\min_i [\varepsilon_i]$$

- Other distances can also be used.
- *Optimal linear dimensionality reducer.*

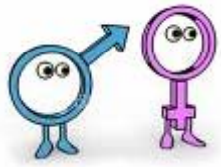


- Supervised method.
- Label information considered.
- Inter-class & Intra class *scatter matrices*; proportional to covariance matrices.

$$J(\mathbf{w}) = \frac{\mathbf{w}^T S_B \mathbf{w}}{\mathbf{w}^T S_W \mathbf{w}}, \quad S_B = \sum_c N_c (\boldsymbol{\mu}_c - \bar{\mathbf{x}})(\boldsymbol{\mu}_c - \bar{\mathbf{x}})^T \quad S_W = \sum_c \sum_{i \in c} (\mathbf{x}_i - \boldsymbol{\mu}_c)(\mathbf{x}_i - \boldsymbol{\mu}_c)^T$$

$$S_W^{-1} S_B \mathbf{w} = \lambda \mathbf{w}$$

- Generalized eigenvalue problem.
- Choice of suitable eigenvalue & eigenvector for the solution.
- Largest eigenvalue is chosen.



- Feature space is divided in two orthogonal subspaces.
- Each sample in training sequence:

$$x_m^i = x_{m,\text{dif}}^i + x_{\text{com}}^i + \varepsilon_m^i, \qquad i = 1, \ldots, C;\ m = 1, \ldots, N_i$$

- Difference subspace is equal to the rank of scatter matrix for each class.

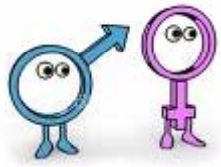
$$x_{\text{com}}^i = x_m^i - P_{RS}^{(i)} x_m^i$$

- Minimizes the criterion:

$$\min \left(\sum_{m=1}^{N_i} \left\| x_m^i - x_{m,\text{dif}}^i - x_{\text{com}}^i \right\|^2 \right)$$

which takes the form:

$$g(x_{\text{test}}) = \arg\min_{i=1,\ldots,C} \left(\left\| x_{\text{test}}^i - x_{\text{com}}^i \right\| \right)$$



- Optimal separating hyper plane.
- Function that predicts best response from some training functions.
- Given, observation-label pairs:

$$(\mathbf{x}_i, y_i), i = 1, \ldots, l$$

- Minimizes the criterion:

$$\min_{\mathbf{w},b,\boldsymbol{\xi}} \quad \frac{1}{2}\mathbf{w}^T\mathbf{w} + C\sum_{i=1}^{l}\xi_i$$

$$y_i(\mathbf{w}^T\phi(\mathbf{x}_i) + b) \geq 1 - \xi_i \quad , \quad \xi_i \geq 0$$

- Kernel function:

$$K(\mathbf{x}_i, \mathbf{x}_j) \equiv \phi(\mathbf{x}_i)^T\phi(\mathbf{x}_j)$$

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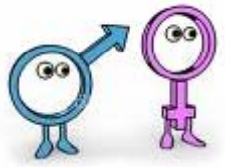

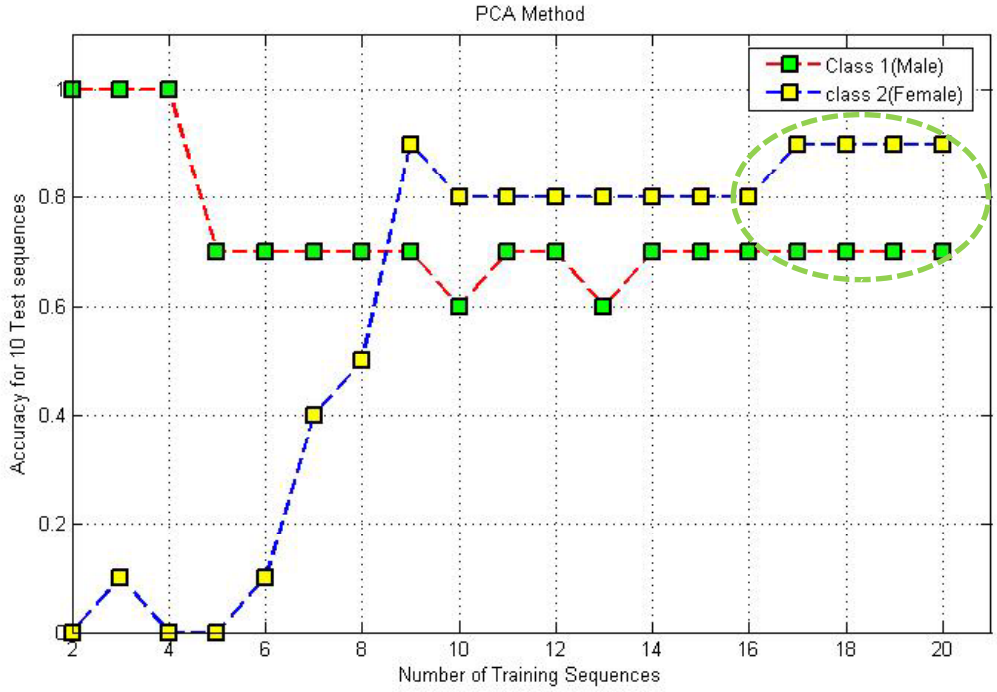

Stability analysis of PCA

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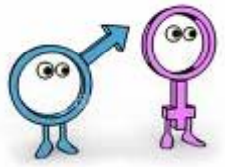

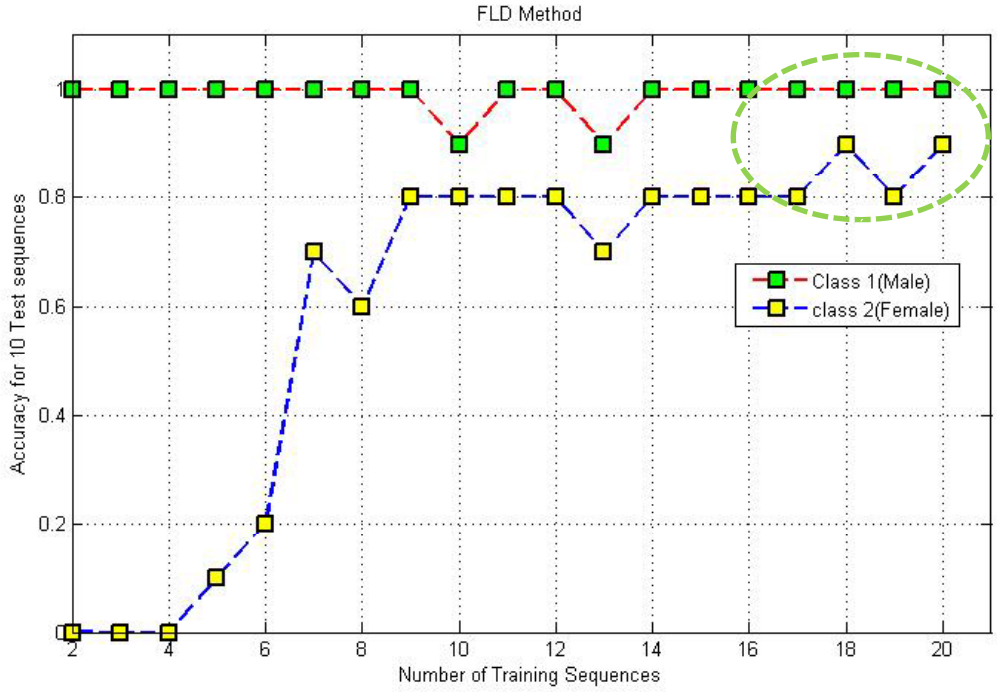

Stability analysis of FLD

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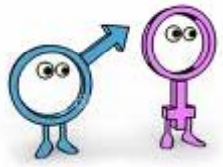

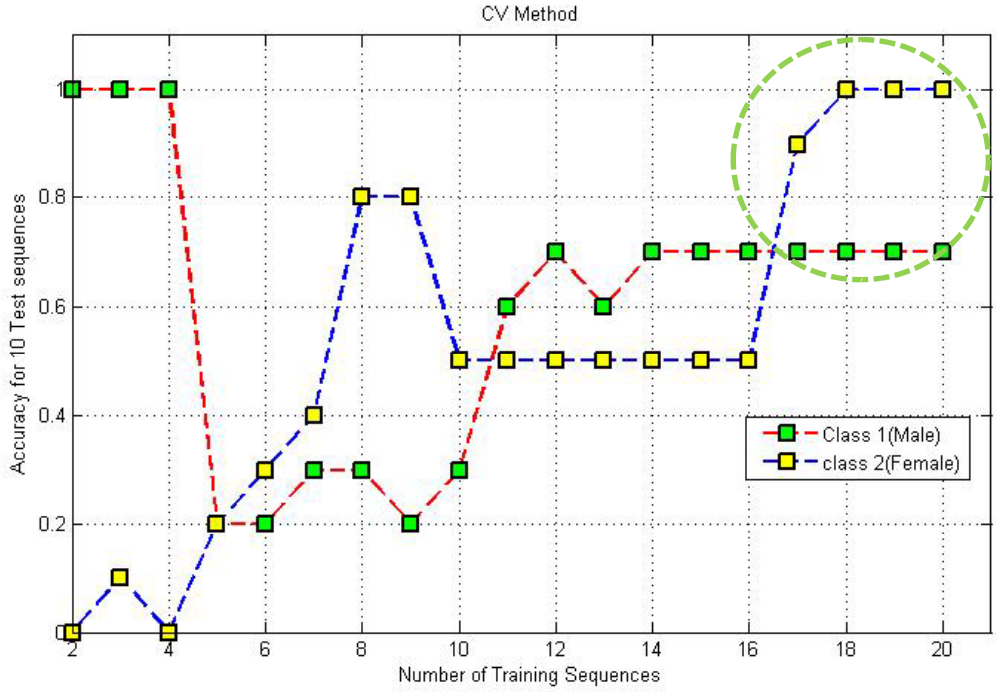

Stability analysis of CV

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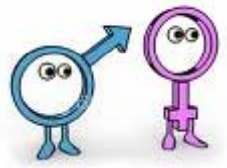

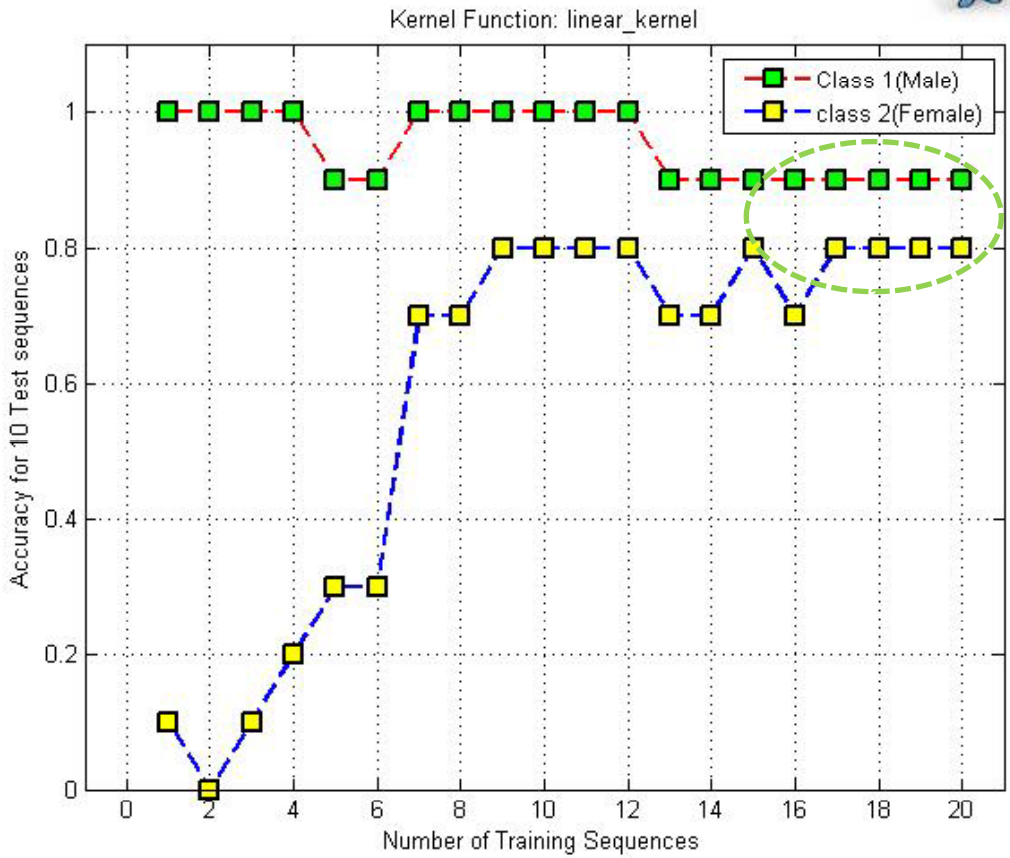

Stability analysis of SVM

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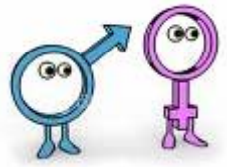

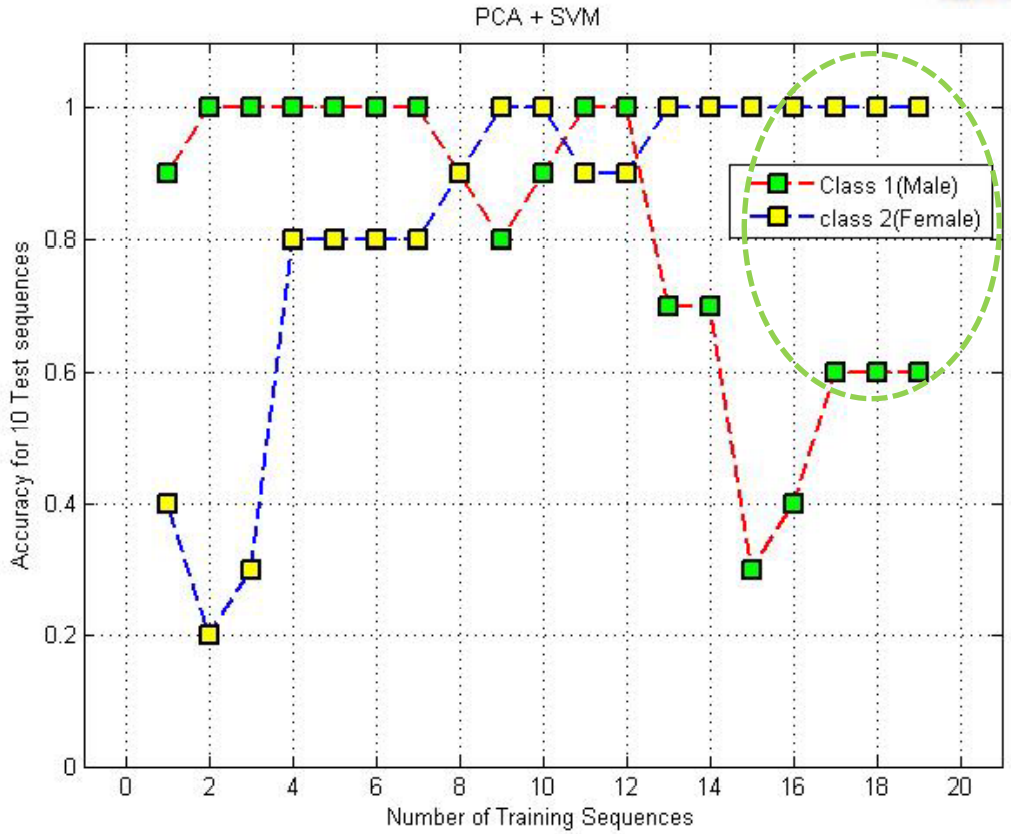

Stability analysis of PCA + SVM

Gender classifier based on Facial information

Accuracy (%age)			
Classifier	Male	Female	Overall
PCA	70	90	80
FLD	**100**	90	**95**
CV	70	**100**	85
SVM	90	80	85
PCA+SVM	60	**100**	80

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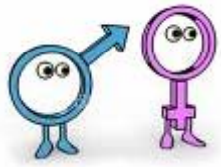
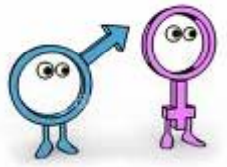


- Thank GOD!! My mind can recognize female faces easily. ☺
- Stability of different methods depends on number of training sequences.
- PCA & SVM prove to be stable and reliable global classifiers with acceptable accuracy.
- Using PCA as dimension reducer and SVM as a classifier can produce better results, if more training sequences can be used.



- Tests with larger databases.
- In depth stability analysis of different global classifiers.
- Other techniques like Neural Networks may be used to validate different conclusions drawn.
- To find a funding source to attend the next summer school. ☺

Thank You!!